California Energy Commission

FINAL PROJECT REPORT

California Investor-Owned Utility Electricity Load Shapes

California Energy Commission

Gavin Newsom, Governor

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PREFACE

The California Energy Commission's Demand Forecasting Unit maintains forecasting models used to develop the Energy Commission's electricity and natural gas demand forecasts. The electric forecast models' output expected annual energy usages by customer sector and geographical zone. The Energy Commission's Hourly Electric Load Model (HELM) converts annual energy use forecasts to hourly demand forecasts by application of appropriate whole-building, end-use, and energy efficiency load shapes. This project updated the HELM and all of its load profiles by coupling hourly load data from investor-owned utilities with analytical and engineering simulation methods.

The California Energy Commission's Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission and distribution and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solutions, foster regional innovation and bring ideas from the lab to the marketplace. The California Energy Commission and the state's three largest investor-owned utilities—Pacific Gas and Electric Company, San Diego Gas & Electric Company and Southern California Edison Company—were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that provide benefits to their electric ratepayers.

The Energy Commission is committed to ensuring public participation in its research and development programs that promote greater reliability, lower costs, and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean, conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently

California Investor-Owned Utility Electricity Load Shapes is the final report under Contract Number300-15-013 conducted by ADM, Associates, Inc. The information from this project contributes to the Energy Research and Development Division's EPIC Program. For more information about the Energy Research and Development Division, please visit the Energy Commission's website at www.energy.ca.gov/research/ or contact the Energy Commission at 916-327-1551.

ABSTRACT

This project updated traditional end-use load shapes for six energy sectors and developed photovoltaic system, light-duty electric vehicle, and energy efficiency load impact profiles, which will be used as inputs for the Demand Analysis Office's California Energy Demand Forecast. The California Energy Commission currently uses the Hourly Electric Load Model to cast annual energy demand forecast elements into hourly demands, from which projected annual peak loads are forecasted. The Hourly Electric Load Model includes weather-sensitive and weather-insensitive load shapes at the end-use, planning area, and forecast zone level for the residential and commercial sectors, and at the whole-building level for other sectors. The project updated end-use load shapes by blending publicly available load shapes from market and metering studies with building simulations in a framework known as EnergyPlus. The project relied on aggregated interval meter data provided by electric investor-owned utilities to calibrate energy simulations and to develop models for other sectors.

The load shapes and profiles developed under this project are dynamic entities within "load shape generators," which can respond to relevant factors such as calendar data, weather data, macroeconomic data, and in some cases, price signals from utility time of use rates. The project also developed software, in the R statistical package, to enable scenario analysis and replace the current Hourly Electric Load Model.

Keywords: California Energy Commission, forecast, load shapes, energy efficiency load impact profiles, Hourly Electric Load Model.

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EXECUTIVE SUMMARY

Introduction

The California Energy Commission (Energy Commission) develops the biennial report the *Integrated Energy Policy Report* (IEPR), an integrated assessment of major trends and issues facing California's energy sector. The IEPR process includes the California Energy Demand Forecast Model (CED Model), a forecast of electricity and natural gas demand for California and a number of planning areas and forecast zones within the state. The CED Model relies on various component models, including the Hourly Electric Load Model (HELM), used to predict annual peak demand by end-use, sector, and planning area. HELM's foundation is based on numerous end-use and whole building hourly load shapes, which are used to cast annual energy use to total hourly demand for each forecast year. These load shapes were last updated (partially) in 2002.

Project Purpose

As part of Agreement Number 300-15-013, the Energy Commission contracted with ADM Associates, Inc. (ADM) to update end-use load shapes, to develop energy efficiency load impact profiles, and to enable analysis related to various load growth, energy efficiency, and weather-based scenarios. The load shapes are used by Energy Commission staff to convert annual energy demand outputs from the California Energy Demand Forecast Model (CED Model) to hourly and peak electric demand forecasts. The project achieved following objectives:

- The project team updated base end-use load shapes by sourcing available secondary data and reconciling those shapes with aggregated whole-building hourly billing data, provided by utility companies.
- The team identified and developed key energy efficiency load impact profiles by using analytical modeling methods and building energy simulations. Energy efficiency load impact profiles differ from base load shapes because they account for interactive effects between internal loads and building heating and cooling systems. They also simulate impacts of controls-related measures that change the utilization schedule of lighting or cooling.
- The team developed additional load profiles to represent electric vehicle charging, and to enable scenario analysis related to customer price response due to time-of-use rates.
- The team developed additional load profiles to represent photovoltaic generation in residential and non-residential sectors.
- The team developed a software infrastructure to adapt load shapes to particular scenarios within the CED Model. This software replaces a portion of the software in the CED Model.

Project Approach

The project followed closely the work plan developed by the Energy Commission in Request for Proposal number 15-322 (2016). The work plan contained the following elements:

- Literature Review
- Development of a Research Plan (referred to as the Analytic Framework)
- Data Gathering
- Baseline Load Shape Development
- Energy Efficiency Load Impact Profiles
- Scenario Analysis
- Documentation, Training, Technology Transfer and Support

At a high level, the project consisted of the following steps:

1. Develop numerous prototypical energy simulation models to describe end-use energy usage for each market sector and forecasting zone
2. Inform the energy simulation models with the most up-to-date and realistic end-use energy intensities and schedules, drawing on resources such as utility interval meter data, the CEUS (Itron, Inc. 2006), the Database for Energy Efficiency Resources (DEER) (Itron, Inc. 2011), and other primary and secondary data related to the characterization of electric end-uses
3. Calibrate the energy simulation models to interval meter data from the representative utility customers
4. Using the calibrated models, simulate energy efficiency measures and technology changes that are expected to occur under the Energy Commission forecasting scenarios
5. Regress over the various model runs above to develop "load shape generators" that can be used to develop energy efficiency impact load shapes and to project load shapes across time
6. Develop a user interface or software framework through which the load shape generators can interact with other components of the CED Model

In addition to load shapes and energy efficiency load impact profiles associated with buildings, ADM also developed load shapes for EV charging and PV generation.

Project Results

The residential sector consists of two main building types: single family and multifamily. There are 24 end-uses in the residential model, including six weather-sensitive end-uses, referred to as heating, ventilation, and air conditioning (HVAC). Load shapes for the six HVAC-related end-uses were generated using utility provided hourly advanced metering infrastructure (AMI) data and a regression-based method to isolate typical non-HVAC loads during weekdays and weekends. This non-HVAC load profile was then subtracted from whole-building load profiles on warmer and colder days to determine cooling and heating load shapes, respectively. A literature review was conducted to source new profiles for the 18 non-HVAC-related end-uses.

The commercial sector consists of 12 different building types. There are 10 end-uses in the commercial sector: three HVAC-related and seven non-HVAC-related end-uses. The three HVAC-related end-uses were generated using building simulation models run in the EnergyPlus simulation framework, which is a whole building energy simulation program maintained by the National Renewable Energy Laboratory (NREL) that models building energy consumption by key end-uses. Because the building models in EnergyPlus reflect individual buildings while the load shapes reflect aggregates of buildings, ADM developed a regression-based calibration method in which multiple simulations were automatically given weights and were thereby aggregated to create more representative load shapes. New load shapes for non-HVAC end-uses were sourced from the last California Commercial End-use Survey (CEUS) (Itron, Inc. 2006). These load shapes were further modified using an hour-matching algorithm intended to modify the load shapes relative to changes in whole building load between the last CEUS and current AMI data.

For the residential and commercial sectors, a residual load shape was developed to capture the systematic differences between the modeled load shapes and the observed AMI data. Although each load shape is relatively accurate, there may still be systematic differences at a whole building level that are not captured on an individual end-use basis. To capture the portion of error that is systematic in nature, for the residential and commercial sector, ADM modeled the residual between the modeled whole building load shape and the observed whole building load shape. The portion that could be modeled systematically was considered an additional end-use hereby known as the residual load shape, while the remaining error was discarded as random.

Unlike the residential and commercial sectors, load profiles for the agricultural, industrial, mining and extraction, and TCU sectors are considered at the whole building level only. For these sectors, the load shapes were modeled via a regression model to create predictive coefficients that could be used to generate accurate load shapes going forward. This regression included temporal factors, such as month, weekday, and hour, as well as other predictors such as cooling degree hours (CDH), economic predictors, and linear growth terms.

Utilities generally rely on rate tariffs to bill street lighting. Therefore, most street lighting remains unmonitored. ADM assumed that street lighting could be broken down into two main components: outdoor lighting fixtures, such as street lamps, and traffic lights. For the proportion of energy use assumed to be attributable to outdoor lighting, ADM used daily sunrise and sunset times to develop a load shape that resembles the daylight-based operation profiles for street lighting. For the proportion of energy usage assumed to be attributable to traffic lights, ADM assigned a flat load shape.

Load shapes for PV generation were generated using the System Advisor Model (SAM)—a performance and financial simulation model for renewable energy sources, developed by NREL. For each forecast zone, a prototypical city was selected, and PV shapes were generated based on several years of historical weather data at different orientations (North, South, East, and West). The results were then consolidated across years best capture a typical weather year. Data from the California Solar Initiative (CSI) was used to aggregate across panel orientations.

Load shapes for light-duty EV charging were created using data from ChargePoint, which is the world's largest network of EV charging stations. These load shapes were created to mimic the Energy Commission's current EV sectors: household vehicles (charging of residential vehicles at residential and non-residential locations), commercial fleet vehicles, and government vehicles. To generate load shapes for EV, ADM created a separate model known as the EV Infrastructure Load Model (EVIL Model). As part of the EVIL Model, ADM also included price elasticity terms to model the impacts of time of use (TOU) rates on EV charging.

In addition to the load shapes described above, ADM also developed energy efficiency load impact profiles based upon a review of the measures included in the last Additional Achievable Energy Efficiency (AAEE), ADM determined that efficiency measures for AAEE could be described by a total of 13 efficiency profiles. ADM relied on EnergyPlus building simulations to generate these efficiency profiles.

Finally, the results of this project culminated in a revised HELM (HELM 2.0), developed by ADM and to be used by the Energy Commission for future forecasts. The HELM 2.0 is a collection of data tables and analysis scripts in the R software environment for statistical computing. The data tables house the regression constants that comprise the dynamic load shape generators, as well as historical and typical weather data, economic data such as gross state products for certain industrial sectors, and tables that map energy efficiency related forecast elements to specific energy efficiency load impact profiles. The HELM 2.0 accepts data in the format of annual energy demands or annual energy savings, and distributes these among all hours of the year to produce hourly energy demands. The hourly results can be viewed and exported at various levels of detail, ranging from a statewide aggregate down to a specific combination of forecast zone, customer sector, and end-use.

Technology Transfer

The primary audience for this project is Energy Commission staff. The updated load shapes and hourly electric load model allows Energy Commission staff to more accurately produce the Demand Forecast Model which is used by utilities, the California Public Utilities Commission, and the California Independent System Operator to inform energy planning and procurement decisions.

The final version of the revised HELM was delivered to the California Energy Commission in February 2019 and will be used to generate the next Integrated Energy

Policy Report. Furthermore, users in the Energy Commission's electrification department started commissioning the revised HELM as their primary data source for end-use load shapes. The Energy Commission has also provided energy efficiency load shapes to public utility companies so that they can use the new load shapes for cost-effectiveness testing.

The results of the Load Shapes project have also been shared with the Southern California Public Power Authority (SCPPA), reducing the amount of utility company resources needed to conduct primary research.

In addition to this final report, information from the Load Shapes project was presented at a Demand Analysis Working Group meeting on July 12, 2018. Slides from this meeting are publicly available at the following website:
http://dawg.energy.ca.gov/meetings/dawg-meeting-electric-vehicle-forecasts

California Benefits

DER technology has advanced significantly over the past decade and current load shapes used to inform the Energy Commission's demand forecast do not account for the current and future deployment of demand-side innovations. Developing improved load shapes will provide an accurate assessment of the contributions of clean energy technologies to reducing peak demand, integrating renewable energy, and maintaining electricity system reliability as the deployment of clean energy technologies and strategies increases over time. This information will be used to improve the Energy Commission's demand forecast and analysis, and identify and target opportunities for future EPIC research funding to further reduce cost, improve safety, and improve reliability.

This project can lead to reduced costs by leading to a more accurate demand forecast for typical usage of appliances and equipment, building type, and implemented demand-side policies. This can lead to more certainty on base-line end-use consumption and provide a better input into the CPUC's Long-Term Procurement Planning efforts so that only the generation that is truly needed, will be planned and procured.

Although the load profiles have been developed primarily for the CED Model, they have found other beneficial applications. As one example, all California Publicly Owned Utilities used the load profiles to conduct cost-effectiveness testing and reporting of their 2018 Energy Efficiency Programs.

CHAPTER 1: Introduction

Project Goals and Background

The Energy Commission contracted with ADM for electric load shape development, which will serve as an input for the CED Model. The goals of the project:

- Provided load shapes for electric end-uses addressed by the CED Model.
- Provided energy efficiency load impact profiles to address how load shapes may be impacted by upcoming efficiency standards, by market and technology changes, and by utility-sponsored energy efficiency programs.
- Enabled projection of load shapes through 2030, accounting for how changes in electric energy use will impact the load shapes.

Project Description

The project followed closely the work plan developed by the Energy Commission in Request for Proposal number 15-322 (2016). The work plan has the following elements:

- Literature Review.
- Development of a Research Plan (referred to as the Analytic Framework).
- Data Gathering.
- Baseline Load Shape Development.
- Energy Efficiency Load Impact Profiles.
- Scenario Analysis.
- Documentation, Training, Technology Transfer and Support.

At a high level, the team did the following steps:

1. Develop numerous prototypical energy simulation models to describe end-use energy usage for each market sector and forecasting zone.

2. Inform the energy simulation models with the most up-to-date and realistic end-use energy intensities and schedules, drawing on resources such as utility interval meter data, the CEUS (Itron, Inc. 2006), the Database for Energy Efficiency Resources (DEER) (Itron, Inc. 2011), and other primary and secondary data related to the characterization of electric end-uses.

3. Calibrate the energy simulation models to interval meter data from the representative utility customers.

4. Using the calibrated models, simulate energy efficiency measures and technology changes that are expected to occur under the Energy Commission forecasting scenarios.

5. Regress over the various model runs above to develop “load shape generators” that can be used to develop energy efficiency impact load shapes and to project load shapes across time.

6. Develop a user interface or software framework through which the load shape generators can interact with other components of the CED Model.

In addition to load shapes and energy efficiency load impact profiles associated with buildings, ADM also developed load shapes for EV charging and PV generation.

Project Approach

This section describes the overall approach taken by ADM. Subsequent chapters detail the methodologies applied to specific project elements.

Load Shape Generators

Most of the load shapes that are available to the industry are static load shapes. These load shapes are static arrays, typically at hourly resolution. The main disadvantage of static load shapes is that they represent one specific scenario. For example, the load shapes from the CEUS (Itron, Inc. 2006) represent loads in one particular year (2002 for the California IOUs) and a particular weather scenario (actual 2002 weather). In applying static load shapes, it is important to be careful that all sourced load shapes are (or are adapted to be) from the same base year and weather scenario. Otherwise, it may be possible to erroneously sum loads from disparate day types and weather conditions.

Energy Commission forecasters use the HELM to generate load shapes for a given year and weather scenario. ADM’s approach to this project is similar to the original HELM. Rather than generating static load shapes, ADM developed and stored regression models and coefficients, which can be converted to full hourly load shapes when coupled to data that represent a particular scenario. The scenario specification could be as simple as specifying a base calendar year, or may require specification of weather data, macroeconomic data such as gross state product (GSP) for certain industrial sectors, or even time-of-use utility rate structures and price-elasticity expectations.

Secondary Data Sources

As part of the scope of the project, ADM was tasked with developing new end-use load shapes for the commercial and residential sectors. The current load shapes used by the Energy Commission in the HELM were last modified in 2002, based on metering data originally collected in the late 1980s. End-use monitoring was not within the scope of the project. Although residential end-uses generally have not significantly changed, ADM reviewed additional resources to identify potential load shapes based on more recent data to supplement the existing load shapes.

For the residential sector, the team reviewed the following data sources to identify prototypical end-use load shapes for use in HELM 2.0:

- Energy Demand Forecast Methods Report (Abrishami et al. 2005)

- Electric Power Research Institute (EPRI) Load Shape Library 4.0 (2016)
- DEER (Itron, Inc. 2011)
- Energy and Environmental Economics, Inc. (E3) Energy Efficiency Calculator (2005)
- End-use Load Research in the Pacific Northwest: Why Now? (Grist 2016)
- Pennsylvania Statewide Act 129: 2014 Commercial & Residential Light Metering Study (GDS Associates, Inc. et al. 2014)
- ADM work products for clients in California, Nevada, and Pennsylvania.

For commercial, ADM reviewed the following data source for use in HELM 2.0:

- CEUS (Itron, Inc. 2006)

The results of this review are discussed in further detail in their respective chapters.

Tuning Shapes to AMI Data

One of the key concerns of using secondary sources as the basis for the commercial and residential load shapes is the potential for underlying changes in behavior or appliance efficiency that may result in significant changes to the load shapes. Generally, ADM anticipated this to be a more significant factor in commercial buildings than residential. Figure 1 provides a hypothetical example of an average daily profile in 2005 compared to an average daily profile in 2014-2016.

Figure 1: Example Comparison of a Whole Building Load in 2005 vs. 2015-2016

Hypothetical comparison of a daily load shape in a building in 2005 compared to a building in 2014-2016.

Source: ADM Associates, Inc.

In general, one can anticipate that the energy use in 2014-2016 has reduced, on average, due to changes in building code and improved energy efficiency. In addition, the peak of the curve is not as pronounced in 2014-2016 relative to 2005. One can make this assumption because the energy efficiency improvements between 2005 and 2014-2016 are likely to be lighting and office equipment-based improvements, which will reduce the relative impact of lighting compared to the other end-use loads and consequently minimize interactive effects in HVAC loads.

Therefore, ADM adapted the load shapes from the CEUS (Itron, Inc. 2006) to match changes in 2014-2016 due to shifts in energy efficiency and to match the load shapes to the building sub-type from the original building type.

To adapt the load shapes, the researchers used the following approach:

1. For a given building sub-type in a given forecast zone, project analysts selected the corresponding major building-type end-use load shapes for the same IOU from the CEUS (Itron, Inc. 2006)—because forecast zones were redesigned between the time of the last CEUS and present day, were not able map the load shapes at a more granular, forecast zone resolution.
2. Outdoor lighting load shapes were developed independently based on historical sunrise/sunset data. Outdoor lighting was then subtracted from the IOU data based on its relative weight as predicted from the Commercial Building Energy Demand Forecast Model.
3. After selecting the appropriate load shape, ADM used the annual demand per end-use for the major building type for that specific forecast zone as predicted by the Commercial Building Energy Demand Forecast Model to estimate the relative weight of each end-use load shape for that building type and forecast zone. The load shapes were then scaled appropriately. Non-HVAC loads were then aggregated to generate an estimate of the 2014 whole-building load shape in absentia of HVAC related loads.
4. Both the IOU load shape for 2014 and the CEUS-based load shape were normalized, and February was isolated as the "base month." This is because February showed the least amount of weather-dependence upon exploratory analysis, suggesting a limited impact of HVAC in this month.
5. After isolating t February for the IOU load shape and the CEUS-based load shape, the project team ran an hour-matching algorithm. This hour-matching algorithm looked at every hour in the IOU load shape relative to its percent of peak in that same day and found its closest match in the corresponding weekday types in the CEUS data. For example, for 1 a.m. Monday, February 3, 2014, the algorithm looked at all Mondays in the CEUS load shape and found the hour it most closely resembled across all Mondays of the CEUS load shape.
6. Table 1 provides an example of the algorithm for a sample 24-hour period.

Table 1: Example of Hour-Matching the 2014-2016 Profile to the 2005 Profile

Hour	Load shape in 2014-2016	Load shape in 2005	Matched Hour
0	0.007057678	0.005268895	0
1	0.007057678	0.005268895	1
2	0.007057678	0.005268895	2
3	0.010038939	0.009992733	3
4	0.020077878	0.019985465	4
5	0.036505232	0.036337209	5
6	0.050194695	0.049963663	6
7	0.060842054	0.060864826	7
8	0.069359942	0.069040698	8
9	0.075444147	0.075399709	9
10	0.077877829	0.07994186	10
11	0.07848625	0.082667151	10
12	0.07848625	0.082667151	10
13	0.077877829	0.07994186	10
14	0.075444147	0.075399709	14
15	0.069359942	0.069040698	15
16	0.060842054	0.060864826	16
17	0.050194695	0.049963663	17
18	0.036505232	0.036337209	18
19	0.020077878	0.019985465	19
20	0.010038939	0.009992733	20
21	0.007057678	0.005268895	21
22	0.007057678	0.005268895	22
23	0.007057678	0.005268895	23

Hypothetical example of hour-matching of a daily load shape in the 2014-2016 whole building load shape to the 2005 whole building load shape.

Source: ADM Associates, Inc.

7. After finding the matched-hour for each hour of the IOU profile, the IOU profile is then disaggregated based on the percent-of-each-end-use present for the matched-hour in the scaled CEUS profile.
8. The February end-use profiles are then extrapolated back to an 8,760-load shape. For the five education-related load shapes, a scaler is applied prior to extrapolating to an 8,760-load shape. Based on the original IOU data, a scaler is generated for the average daily energy use in September divided by the average daily energy use in August. For the months of January through May and September through December, the profiles are scaled relative to the September to August scalar.

Batch Simulations

Tens of thousands of building energy simulations were used to develop the load shapes. This approach has several advantages over a purely statistical approach including modeling interactive effects of efficiency measures, supplementing insufficient meter data for specific building subcategories, explaining anomalous load shapes through simulation experimentation, and exploring physical bounds for load shape limits.

The simulations were done using EnergyPlus and controlled with the R programming language. EnergyPlus was selected because it is highly flexible, well-established simulation software, and can be run from the command line with manually-controlled input files. R was used for the data handling and regressions because it is very effective at statistics at this scale, and it was also used as the scripting language to run EnergyPlus so that the various R scripts could work together. To complete calculations of this scale, five dedicated virtual and physical computers were set up to run months of calculations.

The starting point for the simulation input files were prototypical models taken from the Institute of Electrical and Electronics Engineers (IEEE), and they were modified to represent the building types which constituted the subcategories of the study. The meter data submitted by the IOUs was aggregated from buildings of various sizes, vintages, HVAC types, envelope parameters, etc., and batches of simulations were designed to represent the assortment. Statistical techniques were used to select the weight of each simulation used to find the combination which best matched the meter data. Early in the program, ADM would need over a hundred simulations per building type per climate zone, but over time, ADM learned which parameters had the largest influence on the load shape. ADM learned that setpoint schedules for heating and cooling were very influential and as ADM sought to drive down uncertainty in the most challenging shapes, like schools in the summer, setpoint schedules were the best influence on final load shape.

Dozens of scripts were written to meet the various needs of developing these simulations. These scripts formatted weather files, modified EnergyPlus input files, launched batches of simulations, cleaned results, and did other functions.

Residual Modeling

The load shapes developed for the commercial and residential sectors can be described as either analytically obtained (HVAC load shapes for the residential sector), generated via an engineering simulation (HVAC load shapes for the commercial sector), or obtained from the best currently available resources (non-HVAC load shapes). Although, on an individual basis, each end-use is relatively accurate in nature, there is still potential for variation between the modeled end-uses and the aggregated data. Because the data represents an aggregate of all homes belonging to a certain building-type/forecast zone, it is not readily apparent which specific end-use causes the whole building load to deviate. It is more likely that the deviation stems from an aggregation of minor differences between the modeled end-uses and real-world factors.

Therefore, ADM developed a residual load shape. The residual load shape attempts to recover the component of the residual that is systematic and predictable and acts as a correction factor that bridges the gap between the modeled whole building load and the actual whole building load by providing a relative correction to the modeled whole building. Unlike other load shapes, which are normalized to a total value of one per end-use, the residual load shape is normalized as a percent correction by diving each observation by the total gigawatt hours (GWh) for the base year for the given building-type and forecast zone of interest. It can therefore be reconstituted as a function of the relative intensity of the predicted year by multiplying the normalized profile by the modeled year's total GWh.

ADM generated the residual load shape by taking the actual residuals (difference between the actual AMI data and the modeled loads at each hour) and creating a series of coefficients segmented by time-of-year (month, day-type, and hour) and regressed against CDH/heating degree hour (HDH) for the commercial sector and cooling degree day (CDD)/heating degree day (HDD) for the residential sector. To accomplish this, the analysts first segmented the 8,760 data by its temporal components. For the commercial sector, the analysts segmented by the data by month, day-type (the seven weekday-types plus an additional day-type for holidays), and hour. For the Residential sector, the analysts segmented the data by Pacific Standard Time (PST)/Pacific Daylight Time (PDT), day-type, and hour.

ADM analysts then ran each segment of data through the following regression model:

$$y = \beta_0 + \beta_1 \cdot CDH + \beta_2 \cdot HDH + \varepsilon$$

Where:

- y is the predicted normalized residual
- β_0 is the intercept
- β_1 is the CDH weight (CDD for residential)
- β_2 is the HDH weight (HDD for residential)
- ε is the error term

By modeling the residual using this methodology, ADM has captured the variability remaining that is explainable due to temporal components and weather. The remaining residuals are discarded as random.

Energy Efficiency Load Impact Profiles

The CED Model includes projections for energy savings associated with energy efficiency measures. Energy efficiency gains from various sources are considered and included in the forecast. Energy Commission staff have categorized energy efficiency impacts into committed energy savings and AAEE. Committed savings are those attributable to funded, utility-sponsored energy efficiency programs, to approved building standards, and to approved federal appliance standards. Committed savings are traditionally included in the baseline forecast. AAEE savings include incremental savings from the future market potential identified in utility potential studies, but not included in the baseline demand forecast. AAEE are reasonably expected to occur and include future updates of building codes, appliance regulations, and new or expanded IOU or publicly-owned utility (POU) efficiency programs.

It is conceptually possible to describe committed savings and AAEE at a high level of granularity, for example, energy savings by forecast zone, market sector, building or business type within the market sector, end-use, and specific energy efficiency measure. For example, one may attempt to forecast all energy savings from anti-sweat heat controllers in grocery stores in the coastal portion of SDG&E service territory. It is also possible to develop energy efficiency load impact profiles to couple with specific energy savings expectation. In practice, however, the level of effort with forecasting energy savings at such granularity, let alone coupling such forecast elements to appropriate load impact profiles, would likely be more laborious than the base forecast.

ADM viewed efficiency load impact profile generation and specification as an exercise in efficiency and restraint as much as a demonstration of the modeling infrastructure's capabilities. Rather than generating thousands of energy efficiency load shapes, the team identified the minimal set of load shapes that have the greatest impact on the accuracy of AAEE and committed savings hourly demand impacts. The final framework includes over 1,400 unique energy efficiency load impact profiles, but most of these are building-type and forecast-zone specific variants of eleven energy efficiency load impact profiles. In addition to the 11 archetypal energy efficiency load impact profiles, load shapes are used to characterize energy efficiency savings when appropriate, for example, outdoor lighting load shapes can be used to characterize load impacts for outdoor lighting wattage reductions.

The load shapes for the commercial and residential sectors are generally produced by EnergyPlus models and are then converted to energy efficiency load impact profile generators through regression modeling. End-use load shapes are not available for industrial, agricultural, mining, and extraction sectors, and therefore the whole-building load shape is used as a proxy for AAEE and committed savings for these sectors. This approach is consistent with present Energy Commission practice for these sectors.

In addition to energy efficiency load impact profile development, the project team has developed tables that map line items in recent AAEE and committed savings worksheets used by Energy Commission staff to specific load shapes. ADM has also developed a means to distribute impacts that are generally at the utility/sector/end-use level of resolution, to the requisite model format of utility/forecast-zone/sector/building/end-use/load-shape level. This process is described in Chapter 10.

EV Charging Profiles

Development of load shapes for EV charging was a qualitatively different process than the rest of the work conducted for the project. EV charging load shape development had several unique challenges. For example, a representative sample of clean submeter data for electric vehicle charging is not available from most utility companies. Utility companies do have data from individually metered chargers for residential customers, but those customers are generally a minority of the overall customers that are thought to have electric vehicles. On the other hand, utility companies have demonstrated that

TOU rates effectively induce customers to charge during off-peak hours. Given the expected increased prevalence of TOU rates, historical load shape data may not be representative of future charging profiles. ADM attempted to obtain recent and representative data, but to also anticipate the impacts of increased TOU rate participation. The approach for light duty vehicle charging was to obtain a random sample of charging session data from ChargePoint, and to build in price elasticity response with initial elasticity estimates that reconcile the ChargePoint data to data from pure TOU customers as published in the Joint IOU Electric Vehicle Load Research Report (SDG&E, SCE and PG&E 2017).

Another challenge with determination of personal light duty vehicle charging is that the CED Model forecasts EV charging in terms of total charging energy usage for light duty personal vehicles, yet the rest of the load shape project is in terms of loads at the customer sector and building type level. Personal electric light duty vehicles are charged at home (both in single-family and multifamily settings) and at other destinations, such as workplaces, parking lots, and parking garages. ADM developed tables to disaggregate personal electric light duty vehicle charging into residential and commercial sectors. These tables include open parameters for each forecast zone that can be adjusted by Energy Commission staff as more data becomes available on the charging shares in single-family, multifamily, and commercial sectors.

Unfortunately, charging data for medium-duty and heavy-duty vehicles is not yet readily available. ADM was able to obtain trending data, on a voluntary basis, from some participants of the California Hybrid and Zero Emission Truck and Bus Voucher Incentive Project (HVIP). These load shapes were primarily for municipal bus fleets and smaller commercial shuttle fleets. Charging data for several classes of medium and heavy-duty vehicles are lacking. It is hoped that the recently approved Senate Bill 350 (De León et al. 2015) electrification projects will make available data. ADM decided to develop several "placeholder" load shapes that may be readily updated as more data become available.

PV Generation Profiles

ADM used the SAM[1] to simulate outputs of solar arrays. The SAM can generate hourly outputs for numerous market-available systems, in various orientations and configurations. The output of a particular solar system can depend on various factors, such as geographical location of installation, orientation (in California, south facing arrays tend to generate more energy over the year, but west facing arrays have higher outputs during traditional peak times in late summer afternoons), shading, and tilt. ADM used data collected from CSI rebate applications to determine the average tilt angles, and the percentage of panels installed in each orientation. Residential and

1 The SAM is a renewable energy performance and financial model, develop by NREL. The model can be downloaded at https://sam.nrel.gov/.

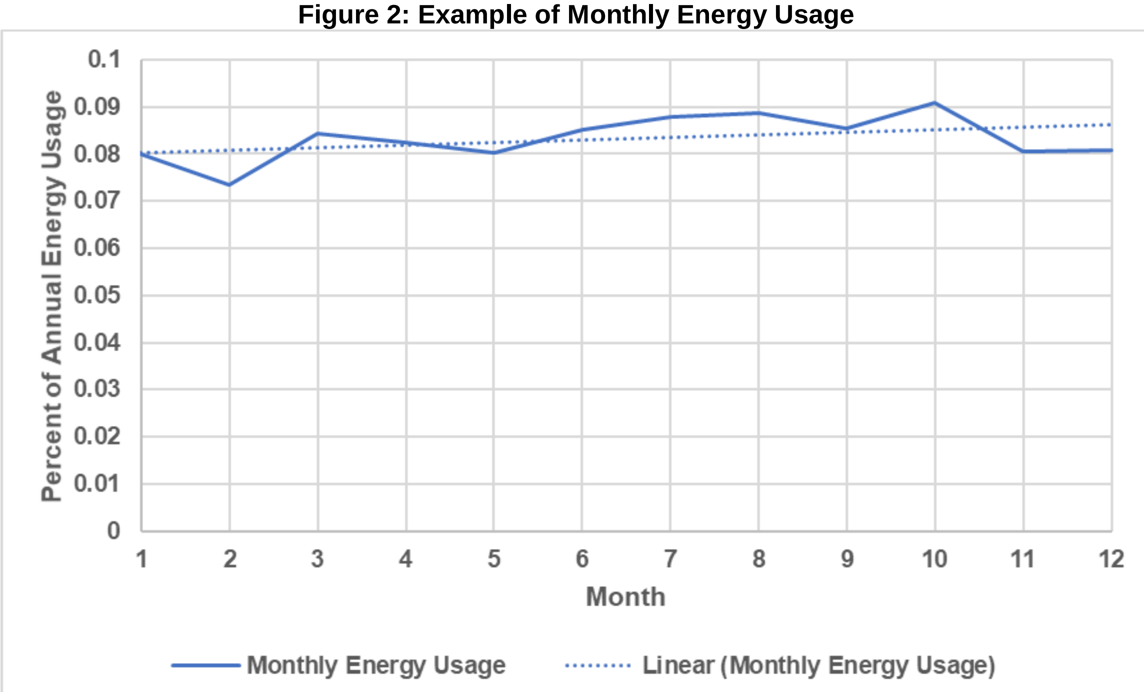
nonresidential have slightly different characteristics with respect to tilt and shading. ADM developed separate load shapes for residential and nonresidential solar generation by climate zone.

Weather and Economic Adjustments

Unlike the commercial and residential sectors, the Energy Commission's load shapes for the agricultural, industrial, mining & extraction, streetlighting, and TCU sectors are not currently generated at the end-use level. Rather, load shapes are currently isolated to the facility-type only. Energy demand in these sectors tend to be process-driven. For example, the load shape for primary metals is driven by the underlying fabrication of primary metals and therefore most end-uses are also tied to that essential load shape. Despite the process-driven nature of energy usage in non-commercial/non-residential sectors, there still may be an underlying correlation between other factors and energy usage in these sectors. For these models, the researchers specifically considered: weather, linear load growth, and economic predictors.

Visual inspection of the monthly load shapes shows some variability over a calendar year which may have some collinearity with temperature. Figure 2 provides an example of a facility-type with energy usage that fluctuates over a calendar year. Energy usage increases during the months of June, July, and August, which suggests an increase in energy use that is collinear with a rise in temperature.

Figure 2: Example of Monthly Energy Usage



Example of monthly energy usage in an Industrial facility-type as taken from logging & derivatives facilities in the 2015 base year.

Source: ADM Associates, Inc.

Because of the seasonal nature of energy use, ADM elected to include a temperature-based term in the regression equation. Although it is unlikely that the increase in energy usage during the summer is tied specifically to HVAC, CDH can be used to approximate collinear variables, such as length of day, seasonal production, etc. The researchers opted to use a CDH term rather than an hourly temperature value to mitigate potential sensitivity as temperature values reach extreme hot or extreme cold values. Using a CDH variable ensures that as the temperature dips towards negative values, the term associated with the weather variable cannot become negative.

ADM also noted significant load growth in the AMI data. As can be seen in **Figure 2**, there is a significant linear relationship between monthly energy usage and the number of months since the origin point (in this case, the origin being January of 2015). Therefore, the researchers included a "day of year" term (with 1 representing January 1st) in the regression equation to include a term to capture the observed linear growth. Although the researchers assume that linear growth will continue to be present going forward, should someone want to exclude linear growth from a generated load shape, modeling the effect as part of the regression allows one to do so.

In addition to linear load growth and temperature-correlated factors, the project analysts also reviewed the impact of economic growth or decline on the resulting load shape. Because production in these sectors are explicitly tied to economic factors, the researchers felt that changes in the economy could predict changes in the load shape for one year compared to another. Therefore, the team included historical economic values as an independent variable in the model. An extract of historical and forecasted economic data obtained from Moody's Analytics, Inc.[2] was supplied by the California Energy Commission for the years 2014 through 2028 at a quarterly resolution by North American Industry Classification System (NAICS) category and forecast zone for the industrial and mining and extraction sectors. The economic data provided for the industrial sector were gross GSP values in units of current-day millions of dollars while the economic data provided for the mining and extraction sector varied between GSP and employment depending on the facility-type. Economic values were provided for TCU at an annual basis and varied between employment and population values.

HELM 2.0

HELM 2.0 has many commonalities with the existing HELM. However, the quantity and types of load shapes differ from those supported by the original HELM, and even corresponding load shapes have different underlying model structures. ADM decided to develop a new software to replace the HELM. The HELM 2.0 is developed in the R statistical programming language. The HELM 2.0 has four major components. The first

2 Moody's Analytics, Inc. is a financial risk management company which specializes both in business solutions and economic forecasting. For the sake of this project, the data obtained as a pass-through from Moody's Analytics, Inc. is comprised primarily of economic insight data regarding forecasted employment levels and GSP levels.

component is a static database of fixed constants associated with the various load shapes. The second component includes input data from other components of the CED Model, as well as scenario-specifics such as weather and economic data. The third component are files that describe a given scenario list the set of load shapes to be run. The fourth component is code that reads in parameters and run-specifications, fetches load shape generator regression coefficients from the database, and performs the arithmetic requires to generate and summarize full load shapes.

Alternate Approaches Considered

The approach to the project follows the analytic framework, developed in December 2016 and revised in March 2017. In the draft framework, the researchers discussed the following alternate approach to the project. The alternate approach would leverage pre-existing load shapes for the commercial and residential sector by specifying existing load shapes from CEUS, DEER, EPRI, and other sources. The advantage of the alternative approach is that cost savings related to load shape disaggregation and simulation would allow for primary data collection regarding emerging technologies and electrification in ports and private and public transportation.

The alternate approach was not selected, in part due to the desire for using recent interval meter data from IOUs to refresh or validate load shapes, and in part to maintain focus on scenario analysis capabilities associated with load shape generators. The project team was able to divert a small portion of the effort to obtain primary and secondary data related to electric vehicle charging, as described in the approach to electric vehicle charging profiles.

CHAPTER 2: Base Load Shapes: Residential Sector

Data Sources

The following section provides a list of the data sources used to generate the residential load shapes. In addition to listing the data source, a brief description of the data source and any data preparation activities are provided.

AMI Data

Pacific Gas & Electric, SCE, and SDG&E provided aggregated 15-minute interval meter data for the years 2014 and 2015 to the Energy Commission as part of the 2017 data request for the IEPR.[3] Data for two of the IOUs was segmented by forecast zone, building type (multi-family homes versus single-family homes), central space heating fuel (gas or electric), and use level (high, medium, and low); resulting in 12 sets of aggregated interval meter data per forecast zone. San Diego Gas & Electric also provided segmented data but excluded a division between single-family and multi-family homes, resulting in six sets of aggregated interval meter data per forecast zone. Data was provided as an averaged load shape, meaning that each observation was an average of all building types belonging to that categorical segment.

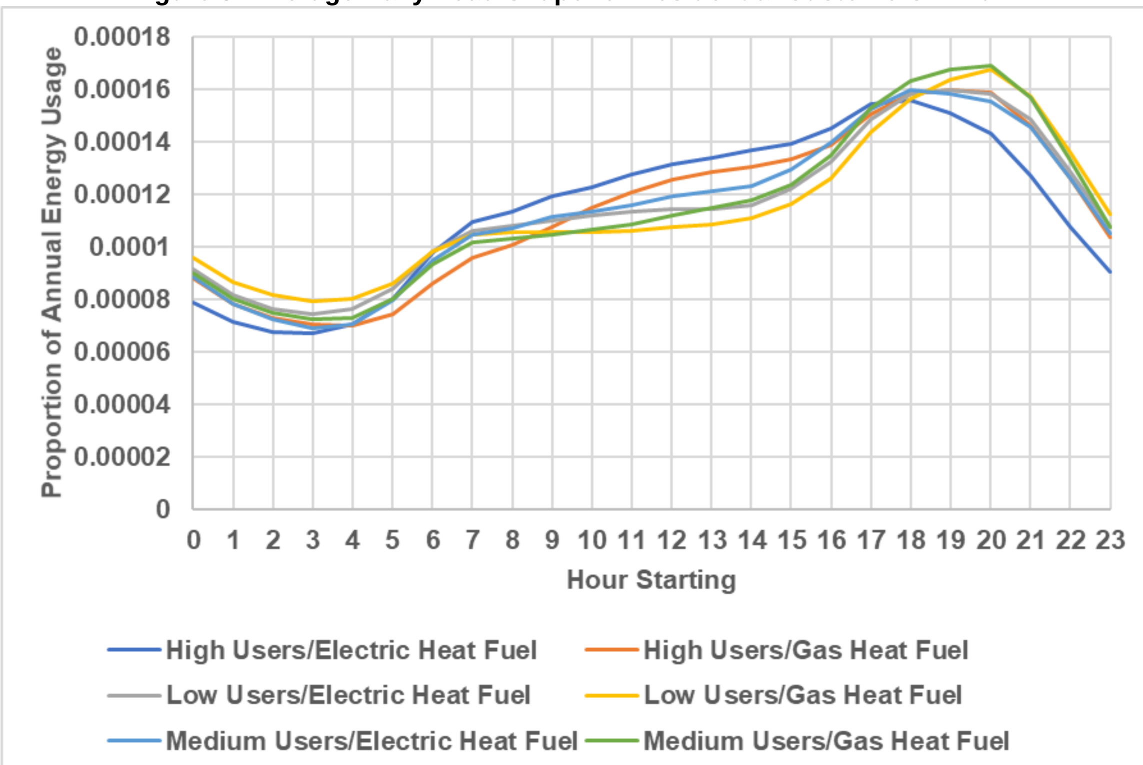
Prior to using the interval meter data, ADM first pre-treated all data. This pre-treatment consisted of standardizing the nomenclature of all files, converting 15-minute data to hourly interval meter data, and merging the dataset with climate-zone specific hourly historical weather data obtained from the Energy Commission. Hourly timestamps were standardized to units of PST for the entire year (specifically 11 p.m. PDT was standardized to 10 p.m. PST). Data was restricted to the period of January 1, 2014 through December 31, 2015.

Exploratory analysis on the AMI data showed potential conflation between electric-heated and gas-heated homes. Specifically, the datasets that were labeled as gas-heated showed were not distinctly different from electric-heated homes. ADM attributes this potential conflation as an overstating of homes that have gas-fuel potential with homes that actively use gas as a fuel source. Furthermore, load shapes did not appear to vary by usage level post-normalization. Given the similarity of the different types of profiles and that the end-uses sources via the meta-analysis did not make a distinction amongst heat fuel or use level, ADM aggregated across the different strata to create one consolidated profile per forecast zone.

3 Aniss Bahreinian et al. *2017 Integrated Energy Policy Report* (2017).

Figure 3 provides an example of an average 24-hour load shape taken from a single forecast zone and building type after the load shapes have been normalized taken across the entirety of 2014. There is high correspondence between all profiles, thereby suggesting that neither heat fuel nor usage level play a significant role in the residential load shape.

Figure 3: Average Daily Load Shape for Residential Customers in 2014



Example of the average daily load shape for all fuel types and energy usage levels for residential customers in a single forecast zone and building type in 2014.

Source: ADM Associates, Inc.

Furthermore, ADM leveraged electric end-use intensities (EUIs), unit energy consumptions (UECs), and forecasted sector-wide electric energy consumption per forecast zone obtained from the CED Model. These values are predicted at a forecast zone level by building type, but not by usage-level. To bridge the relationship between the forecast model and the load shape data, ADM aggregated the IOU data across the three usage levels and scaled the profile to the predicted GWh (exclusive of GWh attributable to PV generation) from the forecast model.

Residential Energy Demand Forecast Model

The Residential Energy Demand Forecast Model is a component of the CED Model which predicts the overall annual energy use for a given end-use at either the forecast zone level (specifically for HVAC end-uses) or at the IOU level (non-HVAC end-uses). The predicted GWh is further subdivided by building type (single family, multifamily, or mobile home). For example, the summary model has predictions of the total annual lighting GWh for all single-family residential buildings in SDG&E service territory, or all single-family cooling for residential buildings in forecast zone 12, etc. Updates are made to the forecast model on an annual basis, with major revisions occurring bi-annually. The Energy Commission corrects its historical load forecast based on observed whole-building energy use on an annual basis, thereby adjusting the end-use level forecast based on the total observed load.

As part of the process of developing load shapes for the base years of 2014 and 2015, ADM leveraged the corrected forecast values for 2014 and 2015 and assumed that the overall energy usage per end-use was distributed in the same proportions as the Residential Energy Demand Forecast Model. Because ADM was interested in the relative percent electric distribution by forecast zone, ADM estimated the total GWh attributed to each forecast zone for non-HVAC end-uses based on population estimates reported as part of the Residential Energy Demand Forecast Model.

Weather Data

An extract of weather data obtained was supplied by the Energy Commission for the years 2014 through 2016. Weather data consisted of outdoor air temperature, dew point, precipitation, windspeed, wind direction, total sky cover, and mean sea level pressure. Weather files were generated for all major airport weather stations (AWS) in California. The Energy Commission provided weighting files meant to define the appropriate weighting of each AWS to generate a forecast-zone-level weather file.

Load Shapes

The current load shapes used by the Energy Commission in HELM were last modified in 2002, based on metering data originally collected in the late 1980s. Although the team did not anticipate significant changes in the end-use profile, the team reviewed additional resources to identify potential load shapes based on more recent data to supplement the existing load shapes. The team reviewed the following data sources to identify prototypical end-use load shapes for use in HELM 2.0:

- Energy Demand Forecast Methods Report (Abrishami et al. 2005)
- Electric Power Research Institute (EPRI) Load Shape Library 4.0 (2016)
- DEER (Itron, Inc. 2011)
- Energy and Environmental Economics, Inc. (E3) Energy Efficiency Calculator (2005)
- End-use Load Research in the Pacific Northwest: Why Now? (Grist 2016)
- Pennsylvania Statewide Act 129: 2014 Commercial & Residential Light Metering Study (GDS Associates, Inc. et al. 2014)
- ADM work products for clients in California, Nevada, and Pennsylvania.

Current Load Shapes

The team reviewed the load shapes used in the Energy Commission's current version of HELM. These load shapes were originally developed in the early 1990s based on metering data from the late 1980s. The load shapes were updated in 2002 by Primen. The current version of the load shape model relies on end-use coefficients that are stored at a monthly by weekday type (weekday or weekend) by hour resolution and then expanded to an 8760-level depending on the calendar year of interest. The coefficients are static - meaning they do not currently interact with any additional inputs such as weather. Internal load shapes are currently the same across forecast zones, while HVAC-related load shapes are different from forecast zone to forecast zone.

The Energy Commission's load shapes do not currently include lighting as one of its current end-uses. As part of ADM's discussions with the Energy Commission, legacy waterbed heater end-use will be depreciated and include a lighting end-use in its place. Load shapes for solar pool pumps, solar water heat - back-up, and solar water heat - pumps are currently flat 8,760 placeholders.

EPRI Load Shape Library 4.0 (2016)

The Load Shape Library 4.0 is a resource developed by the EPRI and publicly available online. The database provides aggregated data from regional utility studies, EPRI proprietary field data, and EPRI CEED (Center for End-Use Energy Data) PowerShapeTM (2000-2001) data. Residential end-use load shape data is presented by North American Electric Reliability Corporation (NERC) region, with the most granular region-specific resolution available being for an aggregated California/Nevada region.

The following non-HVAC residential end-use load shapes are represented in the database:

- Clothes dryer
- Clothes washer
- Dishwasher
- Lighting
- Refrigerator
- Television (TV) & personal computer (PC)
- Water heating

Although some end-use load shapes are available at a region-specific level, several of the above profiles are only presented across all regions. These end-uses include lighting, refrigerators, and TV & PC. Furthermore, all end-uses have been reduced to 24-hour profiles for six day-types:

- Peak season, peak weekday
- Peak season, average Weekday
- Peak season, average Weekend

- Off peak season, peak weekday
- Off peak season, average weekday
- Off peak season, average weekend

DEER (Itron, Inc. 2011)

The DEER is a resource developed by the California Public Utilities Commission (CPUC) to provide information regarding cost, benefit, and ex ante savings for energy efficient measures. Information provided in DEER is gathered from various work papers from the three California electric IOUs (PG&E, SDG&E and SCE).

In 2012, the CPUC made electric savings curved for energy efficiency measures covered by the DEER publicly available for the model year 2013 (DEER 2011). Although these profiles represent efficiency profile, the corresponding end-use load shapes have similar shapes to these efficiency profiles.

There are eight non-HVAC efficiency measures represented in the DEER 2011. The three following items were selected for inclusion as part of the HELM 2.0.:

- Refrigerator/freezer recycling - all space types
- Dishwashers
- Clothes washers

E3 Energy Efficiency Calculator (2005)

The Energy Efficiency Calculator is a resource developed by E3 as an avoided cost tool for the three California IOUs in response to CPUC proceeding R.04-04-025. The original version of the E3 Energy Efficiency Calculator relies on load shapes derived from a 1994 metering study. Versions of the calculator developed after 2008 supplants these load shapes with load shapes derived from DEER. The benefit of the 1994 profiles lies in the use of primary data collection for development. For this study, ADM will rely on the load shapes developed through the 1994 study and reported secondarily by E3.

The following non-HVAC end-uses are represented in the 2005 E3 Energy Efficiency Calculator:

- Clothes dryers
- Freezers
- Microwaves
- Pool pumps
- Refrigerators
- Stove/Oven
- Spa/Hot Tub/Spa Heater
- Stove only
- Water heater

- Clothes washer

Profiles for the above end-uses were derived from metering data across multiple climate zones (2-5, 11-13, and 16). Large sample sizes were used for the generation of most end-use load shapes, except for spa/hot tub/spa heater and pool pumps (10 participants each).

Additional Work Products

In addition to the previously identified resources, ADM reviewed work products previously produced for clients in Nevada and Pennsylvania as additional lighting load shape resources. These studies were based on residential lighting metering done in 2015 in sites in Ohio and Pennsylvania. Additionally, ADM reviewed a work product developed in 2016 for a client in California that generated load shapes for variable speed drive (VSD) pool pumps and single-speed/two-speed pool pumps based on a combination of spot-measurements and operating schedules collected via on-site data collection.

Source Selection/Weighting Methodology: Internal Loads

As mentioned in the discussion of residential data sources, ADM conducted a literature review to find updated sources for non-HVAC end-use load shapes. The load shapes related to heating, cooling, and furnace fans were created using a shoulder-weather extraction method. This approach is described in greater detail in their respective sub-sections.

For the non-HVAC end-use load shapes, ADM assessed the load shapes to ensure that the shapes were consistent with theoretical assumptions regarding how the load shape should typically look in a 24-hour span during different times of year. Specifically, ADM considered how the average daily load shape for weekdays and weekends looked during each of the four seasons. Additionally, ADM reviewed how the load shapes varied in terms of the predicted energy use on a monthly basis and determined whether each load shape behaved consistently with expectations regarding how end-use energy use should vary on a monthly basis.

After reviewing load shapes from each of the sources per end-use, ADM aggregated across all valid sources to create a single load shape per end-use. It is important to note that many of the sourced load shapes have stored their profiles at an 8,760 resolution. Storing a profile at an 8,760 resolution has some advantages in that it increases the precision with which it models the year in which it was based upon. However, the predictive capability of such a load shape may be compromised as the conditions of a year in which someone is attempting to predict the end-use load may vary on a daily basis from the base year. This potential model error dissipates when looking at lower resolution periods of time as the error of an individual observation becomes canceled out by error from a different observation, assuming that error is random. Therefore, once ADM created a consolidated load shape for a given end-use, ADM compressed the load shape by taking the average daily load shape for a day-type (the seven standard weekdays and holidays) in each month.

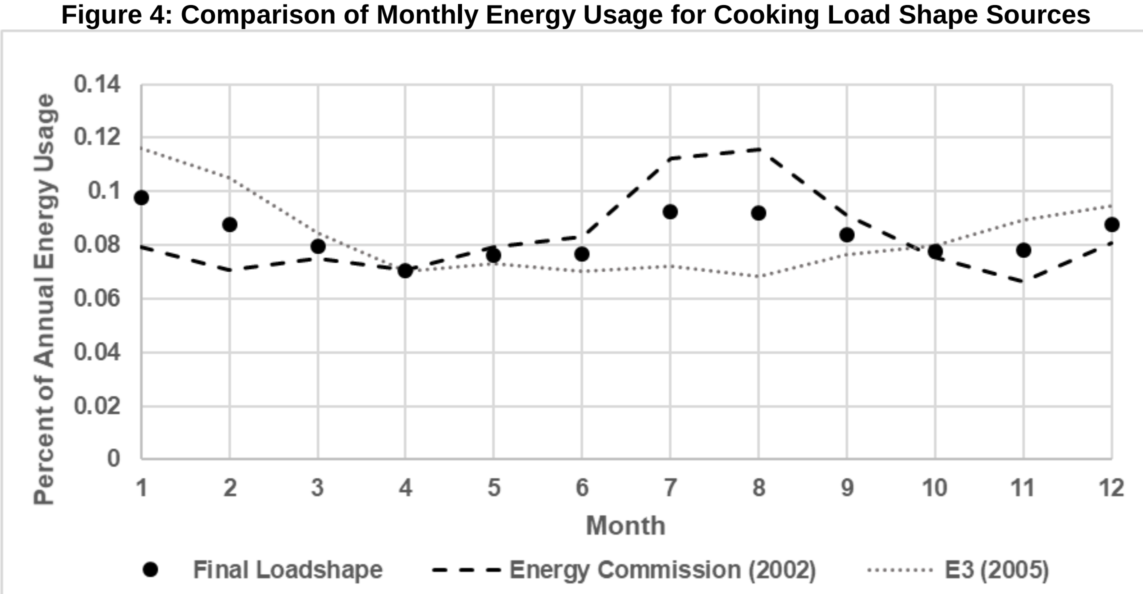
In addition to the load shapes that are described, the Energy Commission also lists three solar load shapes as part of their CED Model. These solar load shapes are: solar pool pump, solar water heat – back-up, and solar water heat – pump. The expected energy use for all three end-uses is effectively negligible, comprising less than 0.1% of the total energy use each year in a given forecast zone. Therefore, a simple substitution was made for each of the three load shapes. solar pool pumps utilized a flattened version of the pool pump load shape (flattened by averaging the Pool Pump shape with a flat load shape). The solar water heat – back-up load shape used the water heating load shape. Finally, the solar water heat – pump load shape used a simple flat load shape.

The remainder of this section will present the non-HVAC load shapes that were sourced via the secondary data sources and describe and present the method for extracting HVAC load shapes.

Cooking

The team reviewed two sources for the cooking end-use: the Energy Commission's existing load shape, as updated in 2002; and an aggregate of all profiles related to cooking as presented in E3's Energy Efficiency Calculator (2005). Figure 4 through Figure 12 present the monthly energy use and seasonal weekday/weekend daily profiles for both sources and the aggregated load shape. In general, the average daily load shapes appeared consistent with one another regardless of the season. Although the monthly energy usage differed from one another, an argument could not be made as to why one profile may be more valid than the other, therefore, ADM averaged both profiles together to create the final load shape.

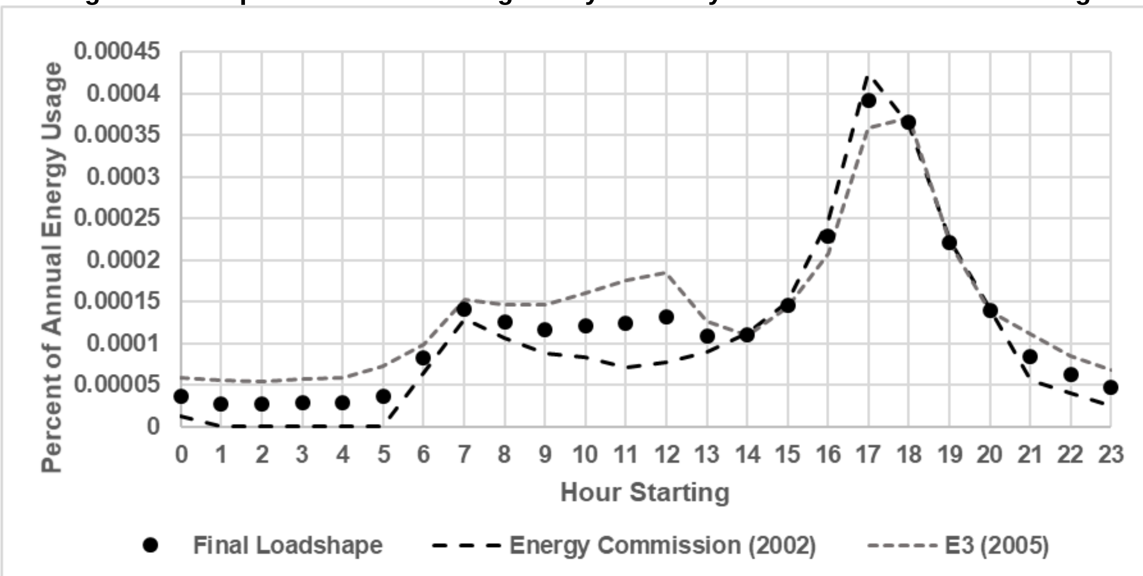
Figure 4: Comparison of Monthly Energy Usage for Cooking Load Shape Sources



A comparison of the monthly energy use for the cooking end-use as predicted by the Energy Commission's 2002 load shape and the aggregation of all cooking loads as presented in the E3 Energy Efficiency Calculator in units of percent.

Source: ADM Associates, Inc.

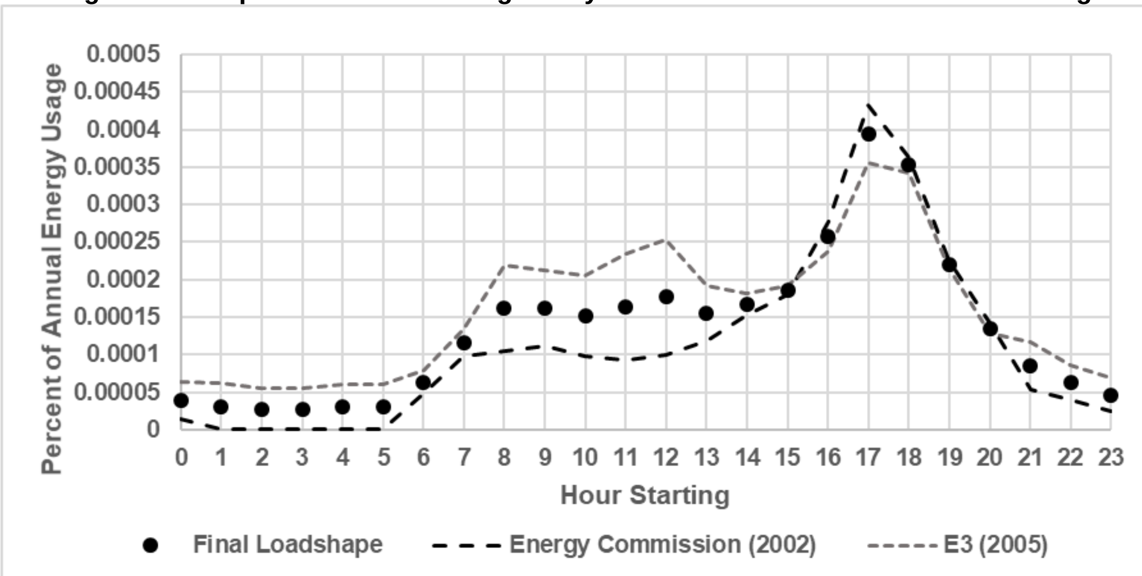
Figure 5: Comparison of the Average Daily Weekday Profile in Winter for Cooking



A comparison of the average daily load shape in weekdays in winter for the cooking end-use as predicted by the Energy Commission's 2002 load shape and the aggregation of all cooking loads as presented in the E3 Energy Efficiency Calculator in units of percent.

Source: ADM Associates, Inc.

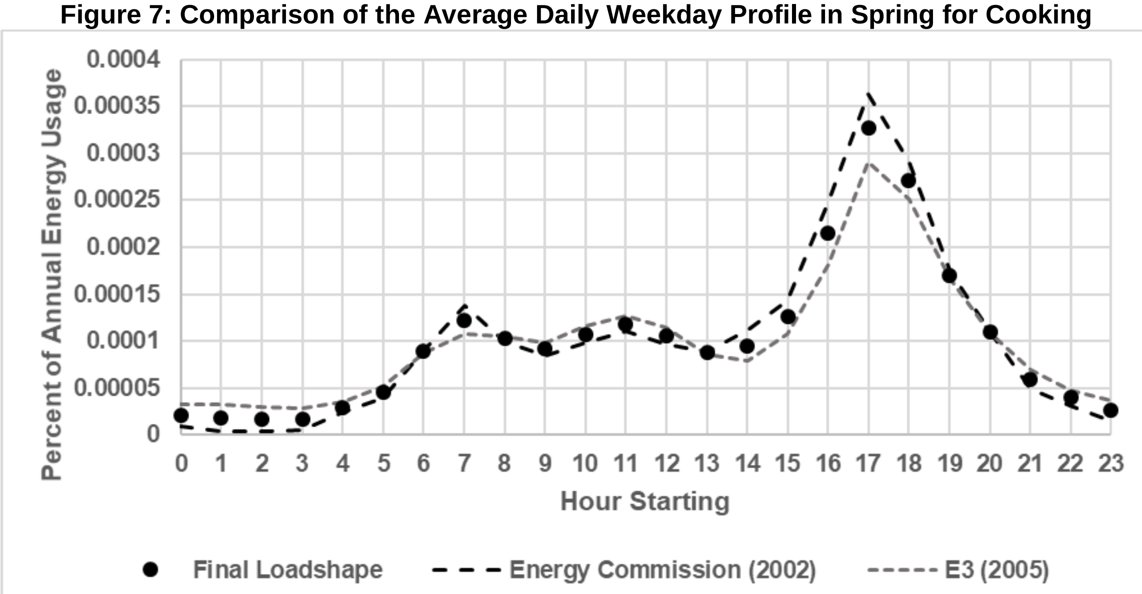
Figure 6: Comparison of the Average Daily Weekend Profile in Winter for Cooking



A comparison of the average daily load shape in weekends in winter for the cooking end-use as predicted by the Energy Commission's 2002 load shape and the aggregation of all cooking loads as presented in the E3 Energy Efficiency Calculator in units of percent.

Source: ADM Associates, Inc.

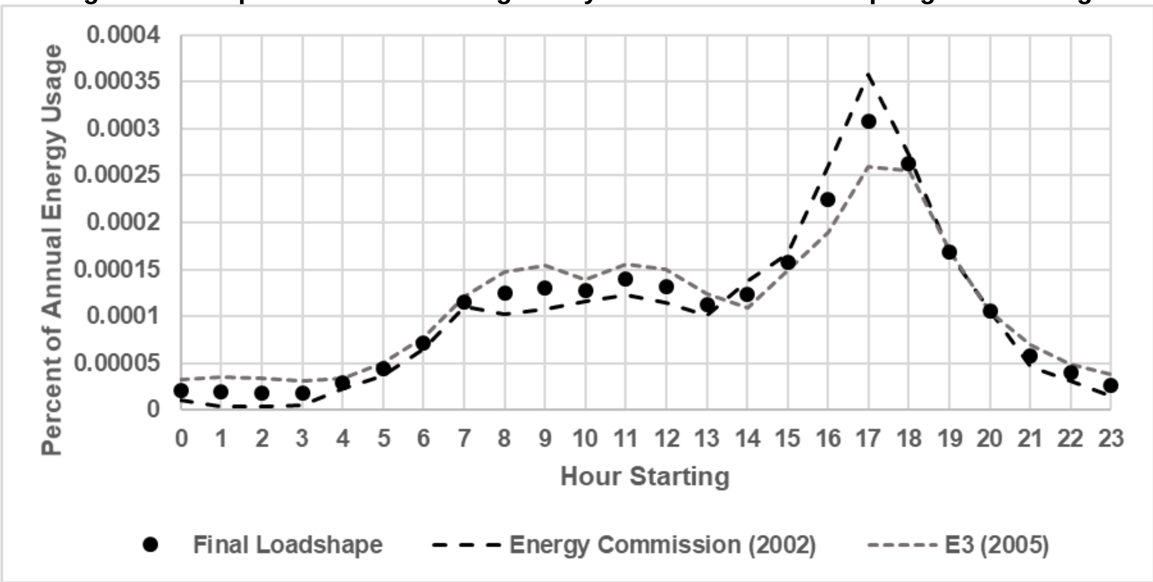
Figure 7: Comparison of the Average Daily Weekday Profile in Spring for Cooking



A comparison of the average daily load shape in weekdays in spring for the cooking end-use as predicted by the Energy Commission's 2002 load shape and the aggregation of all cooking loads as presented in the E3 Energy Efficiency Calculator in units of percent.

Source: ADM Associates, Inc.

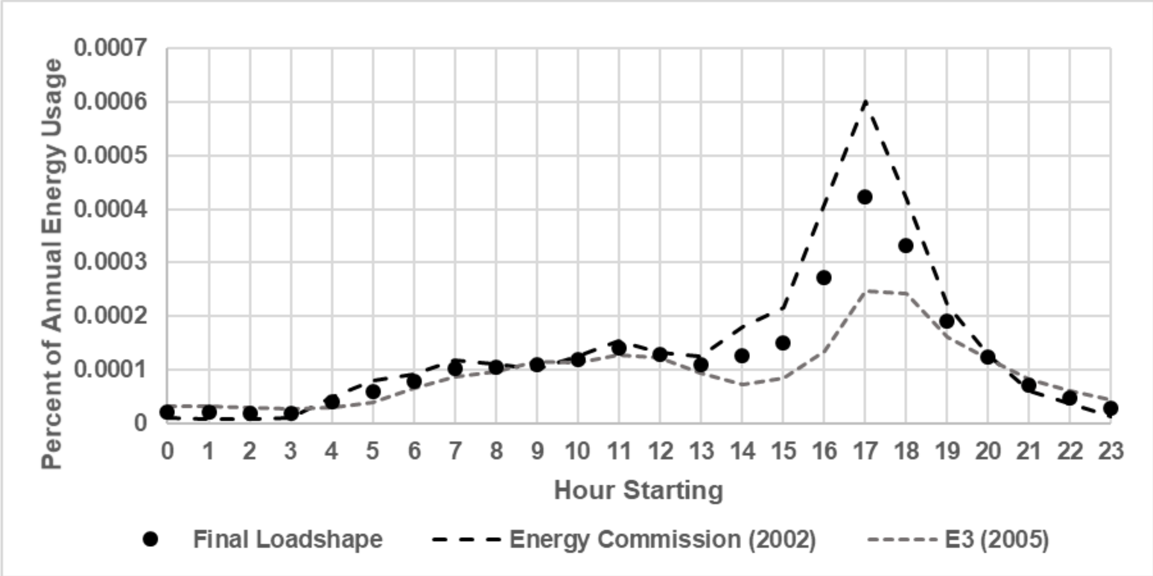
Figure 8: Comparison of the Average Daily Weekend Profile in Spring for Cooking



A comparison of the average daily load shape in weekends in spring for the cooking end-use as predicted by the Energy Commission's 2002 load shape and the aggregation of all cooking loads as presented in the E3 Energy Efficiency Calculator in units of percent.

Source: ADM Associates, Inc.

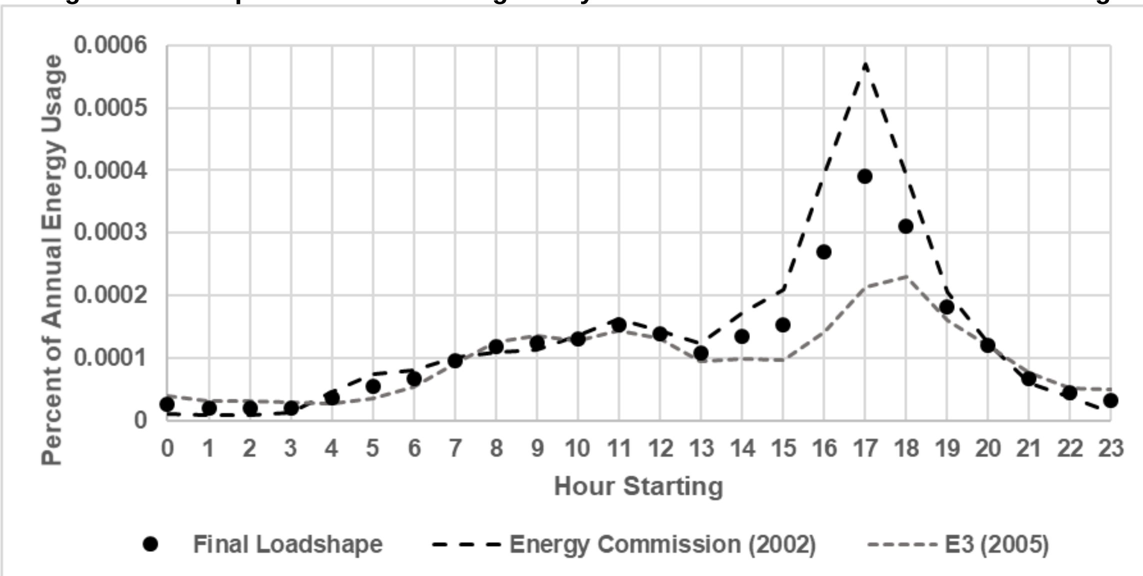
Figure 9: Comparison of the Average Daily Weekday Profile in Summer for Cooking



A comparison of the average daily load shape in weekdays in summer for the cooking end-use as predicted by the Energy Commission's 2002 load shape and the aggregation of all cooking loads as presented in the E3 Energy Efficiency Calculator in units of percent.

Source: ADM Associates, Inc.

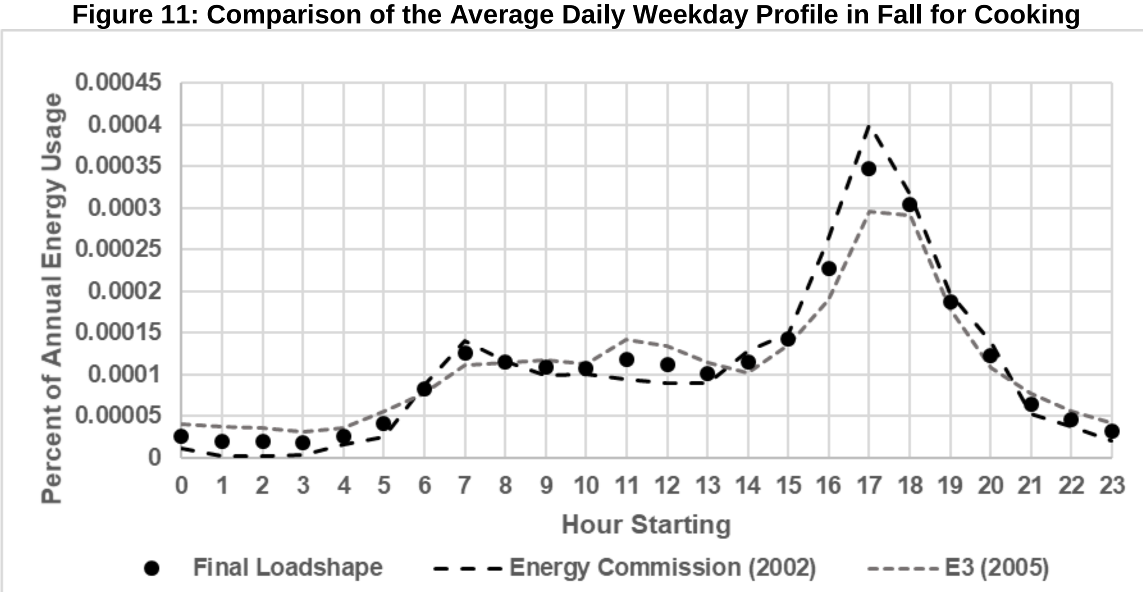
Figure 10: Comparison of the Average Daily Weekend Profile in Summer for Cooking



A comparison of the average daily load shape in weekends in summer for the cooking end-use as predicted by the Energy Commission's 2002 load shape and the aggregation of all cooking loads as presented in the E3 Energy Efficiency Calculator in units of percent.

Source: ADM Associates, Inc.

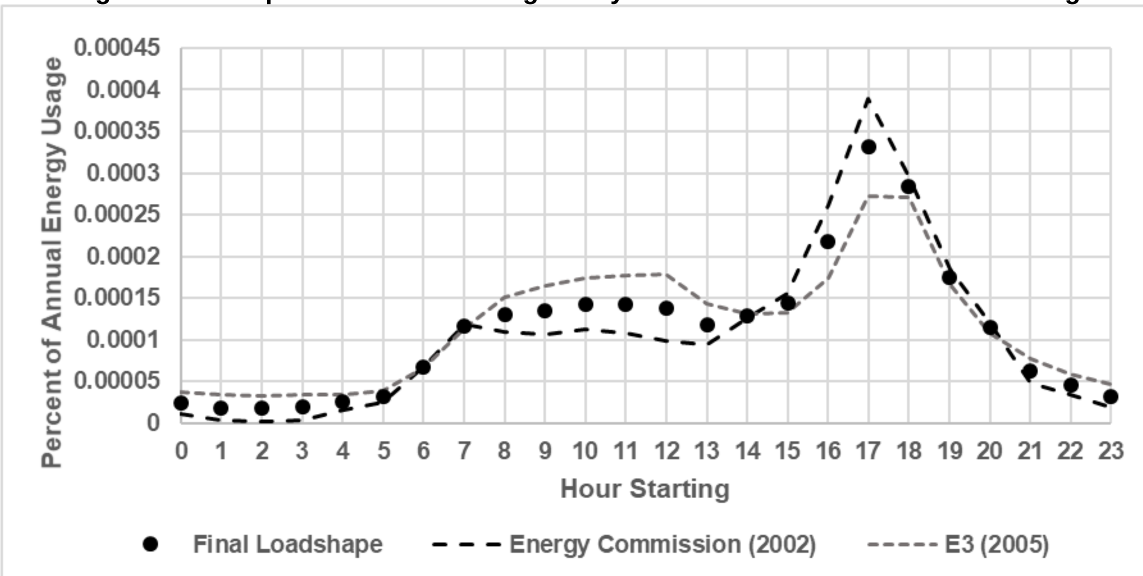
Figure 11: Comparison of the Average Daily Weekday Profile in Fall for Cooking



A comparison of the average daily load shape in weekdays in fall for the cooking end-use as predicted by the Energy Commission's 2002 load shape and the aggregation of all cooking loads as presented in the E3 Energy Efficiency Calculator in units of percent.

Source: ADM Associates, Inc.

Figure 12: Comparison of the Average Daily Weekend Profile in Fall for Cooking



A comparison of the average daily load shape in weekends in fall for the cooking end-use as predicted by the Energy Commission's 2002 load shape and the aggregation of all cooking loads as presented in the E3 Energy Efficiency Calculator in units of percent.

Source: ADM Associates, Inc.

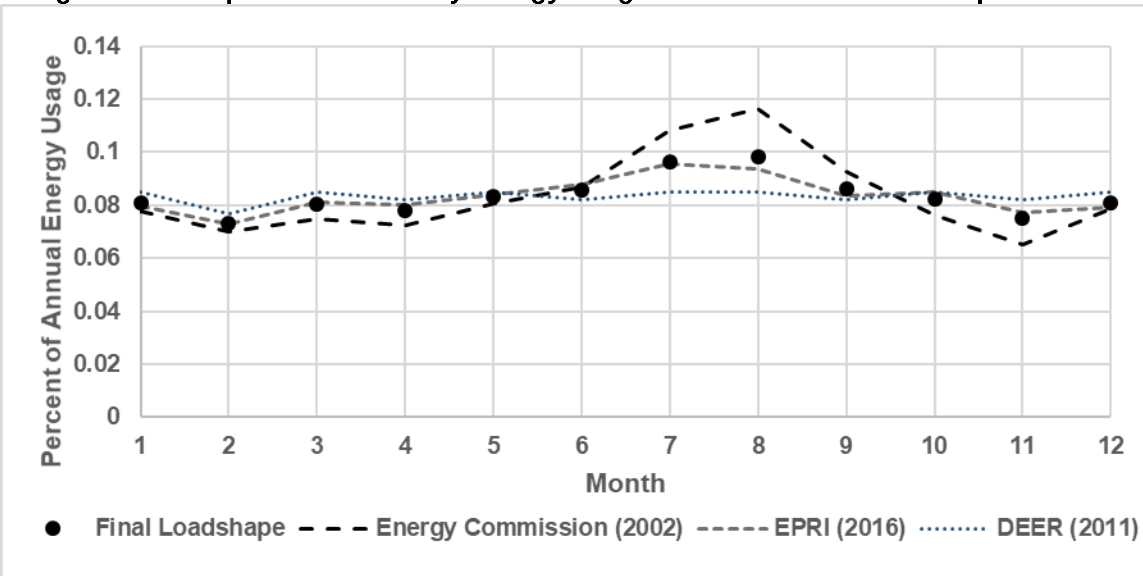
Dishwasher

The team reviewed two sources for the dishwashing end-use: the Energy Commission's existing load shape, as updated in 2002; the EPRI Load Shape Library 4.0 (2016); and the DEER load shape (Itron, Inc. 2011).

Figure 13 through

Figure 21 present the monthly energy usage and seasonal weekday/weekend daily profiles for both sources and the aggregated load shape. In general, the average daily load shapes appeared consistent with one another regardless of the season. Although the monthly energy usage differed from one another, an argument could not be made as to why one profile may be more valid than the other, therefore, ADM averaged all profiles together to create the final load shape.

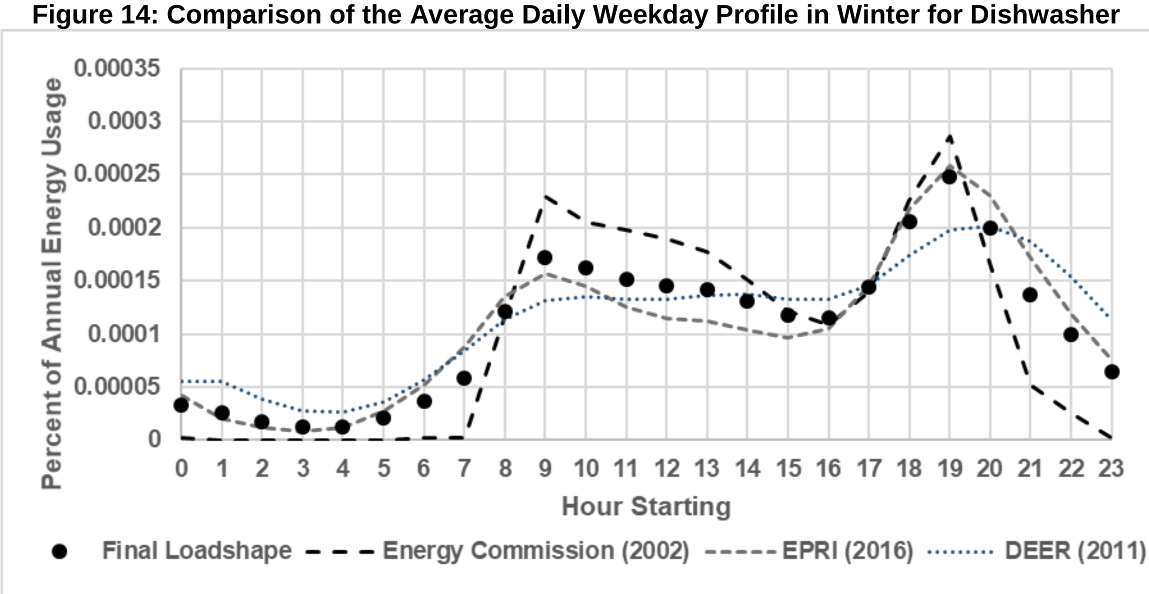
Figure 13: Comparison of Monthly Energy Usage for Dishwasher Load Shape Sources



A comparison of the monthly energy usage for the dishwasher end-use as predicted by the Energy Commission's 2002 load shape, the EPRI (2016) load shape, and the DEER (Itron, Inc. 2011) load shape.

Source: ADM Associates, Inc.

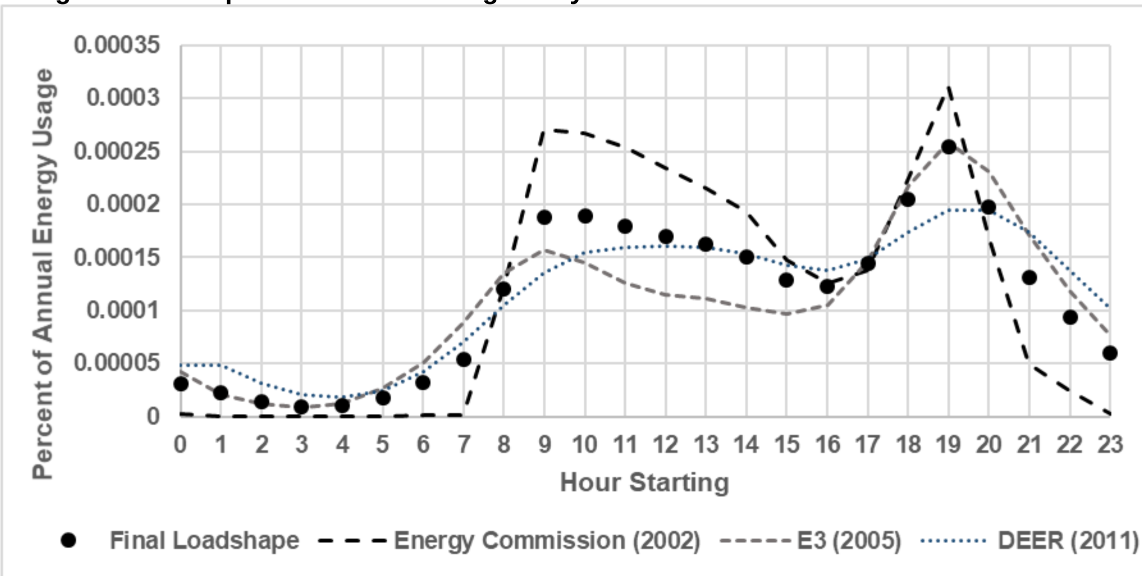
Figure 14: Comparison of the Average Daily Weekday Profile in Winter for Dishwasher



A comparison of the average daily load shape in weekdays in winter for the dishwasher end-use as predicted by the Energy Commission's 2002 load shape, the EPRI (2016) load shape, and the DEER (Itron, Inc. 2011) load shape.

Source: ADM Associates, Inc.

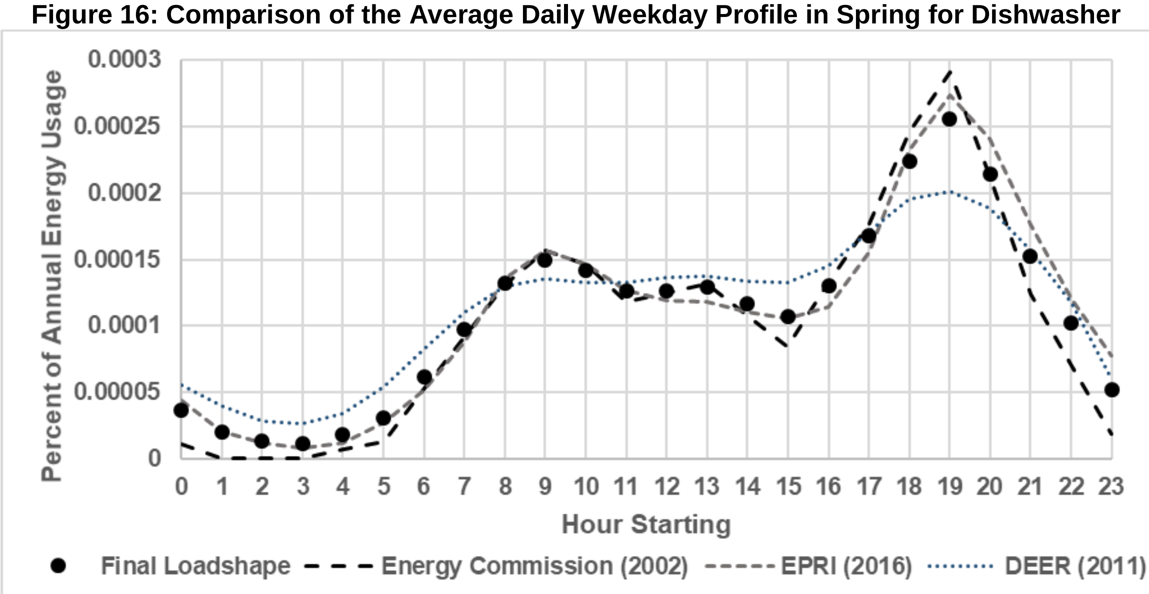
Figure 15: Comparison of the Average Daily Weekend Profile in Winter for Dishwasher



A comparison of the average daily load shape in weekends in winter for the dishwasher end-use as predicted by the Energy Commission's 2002 load shape, the EPRI (2016) load shape, and the DEER (Itron, Inc. 2011) load shape.

Source: ADM Associates, Inc.

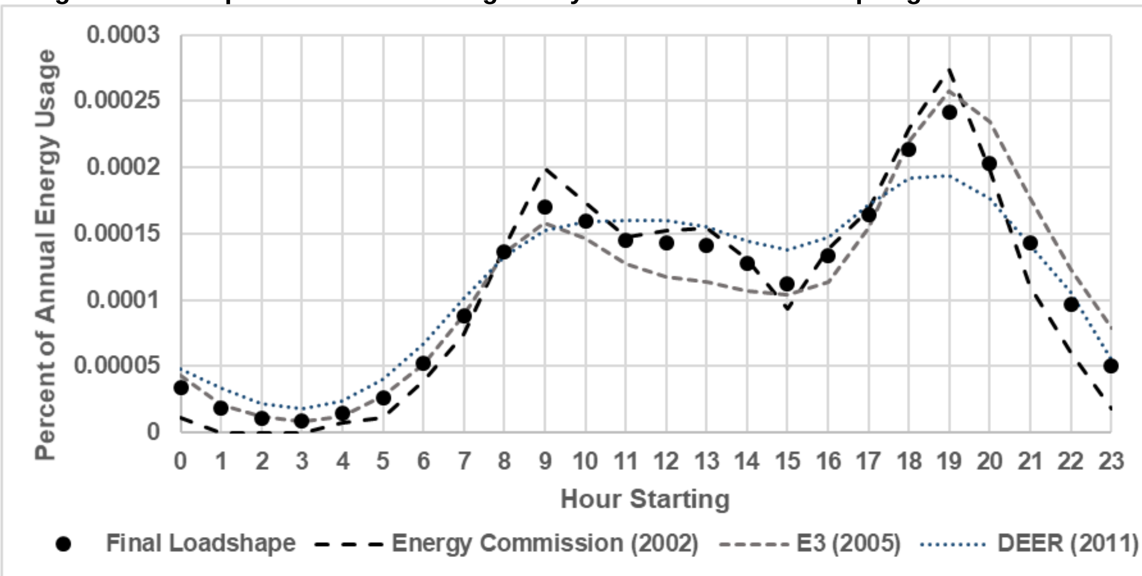
Figure 16: Comparison of the Average Daily Weekday Profile in Spring for Dishwasher



A comparison of the average daily load shape in weekdays in spring for the dishwasher end-use as predicted by the Energy Commission's 2002 load shape, the EPRI (2016) load shape, and the DEER (Itron, Inc. 2011) load shape.

Source: ADM Associates, Inc.

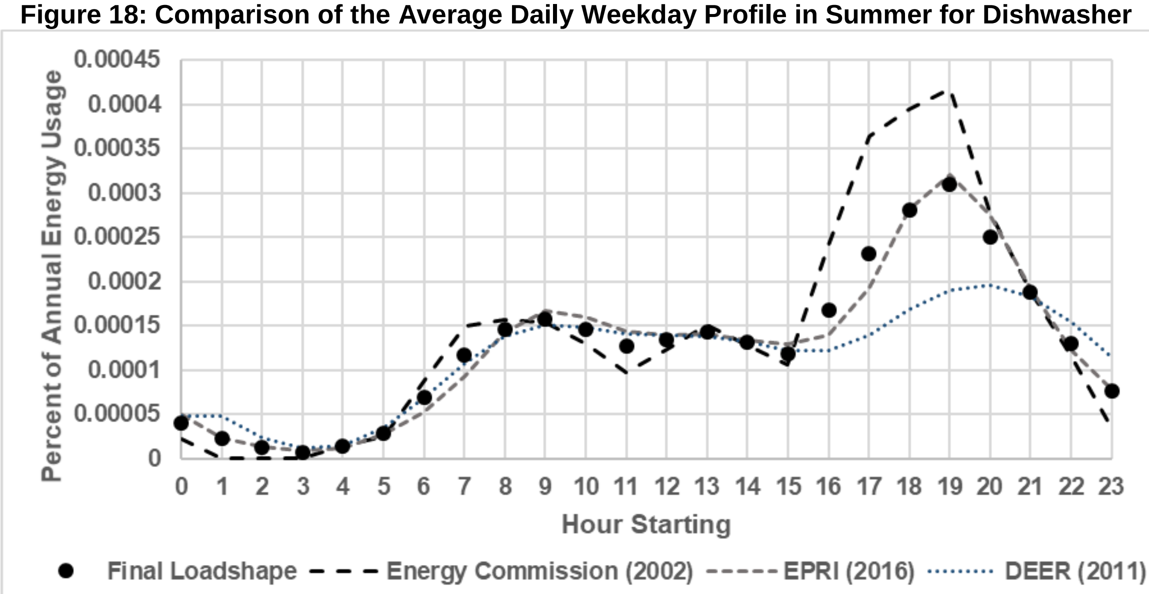
Figure 17: Comparison of the Average Daily Weekend Profile in Spring for Dishwasher



A comparison of the average daily load shape in weekends in spring for the dishwasher end-use as predicted by the Energy Commission's 2002 load shape, the EPRI (2016) load shape, and the DEER (Itron, Inc. 2011) load shape.

Source: ADM Associates, Inc.

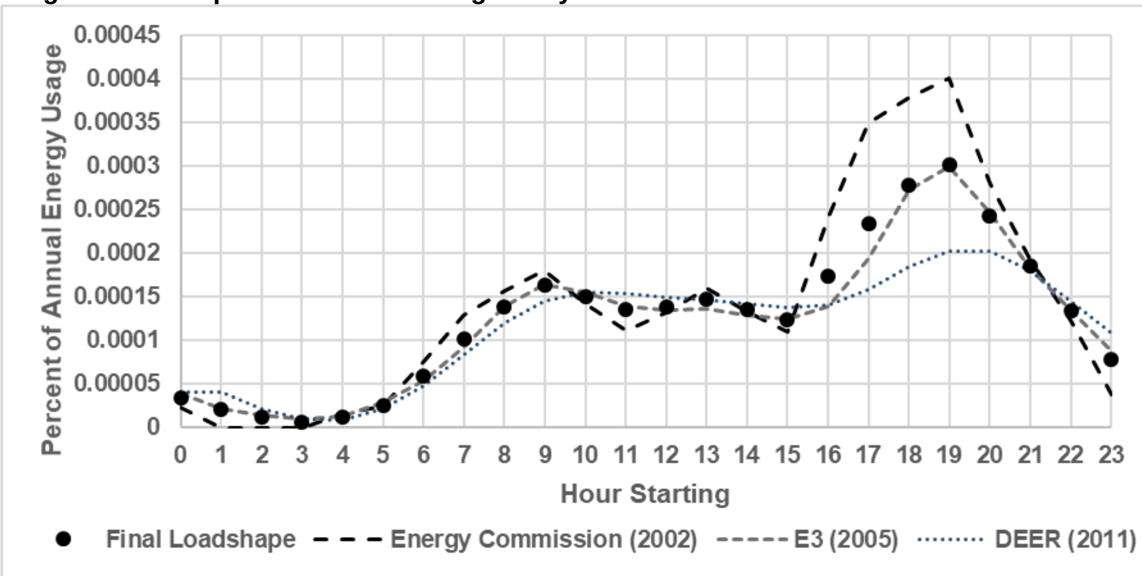
Figure 18: Comparison of the Average Daily Weekday Profile in Summer for Dishwasher



A comparison of the average daily load shape in weekdays in summer for the dishwasher end-use as predicted by the Energy Commission's 2002 load shape, the EPRI (2016) load shape, and the DEER (Itron, Inc. 2011) load shape.

Source: ADM Associates, Inc.

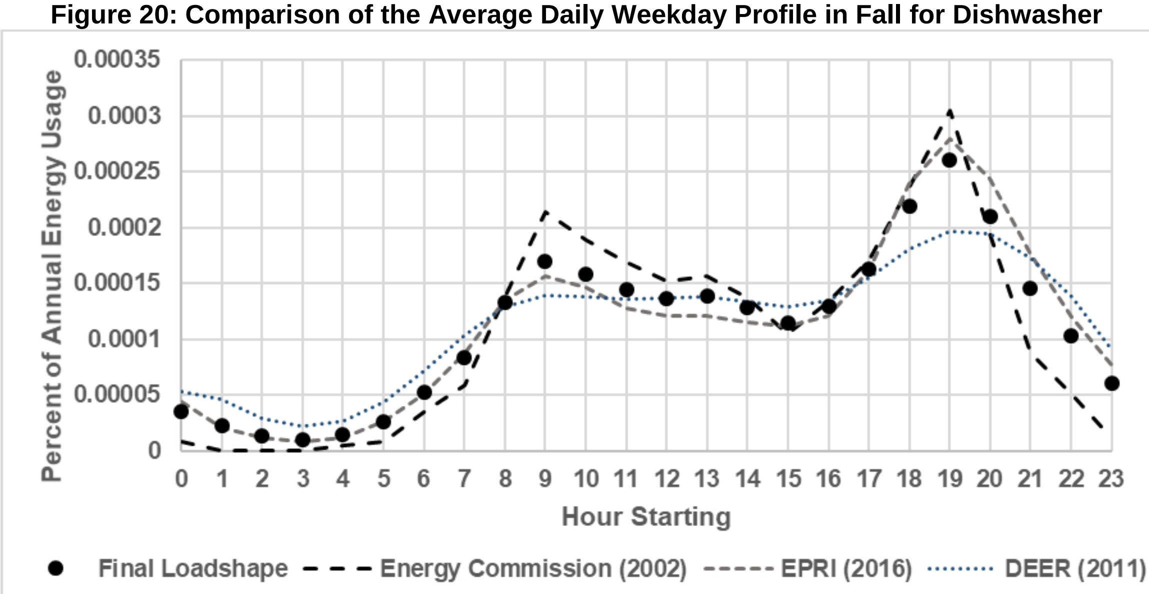
Figure 19: Comparison of the Average Daily Weekend Profile in Summer for Dishwasher



A comparison of the average daily load shape in weekends in summer for the dishwasher end-use as predicted by the Energy Commission's 2002 load shape, the EPRI (2016) load shape, and the DEER (Itron, Inc. 2011) load shape.

Source: ADM Associates, Inc.

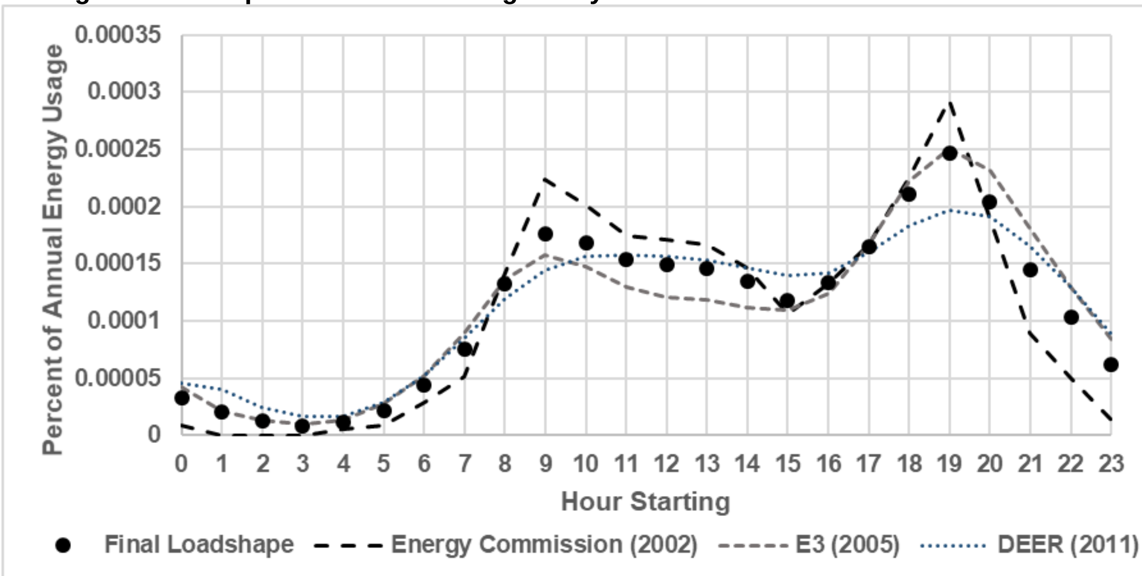
Figure 20: Comparison of the Average Daily Weekday Profile in Fall for Dishwasher



A comparison of the average daily load shape in weekdays in fall for the dishwasher end-use as predicted by the Energy Commission's 2002 load shape, the EPRI (2016) load shape, and the DEER (Itron, Inc. 2011) load shape.

Source: ADM Associates, Inc.

Figure 21: Comparison of the Average Daily Weekend Profile in Fall for Dishwasher



A comparison of the average daily load shape in weekends in fall for the dishwasher end-use as predicted by the Energy Commission's 2002 load shape, the EPRI (2016) load shape, and the DEER (Itron, Inc. 2011) load shape.

Source: ADM Associates, Inc.

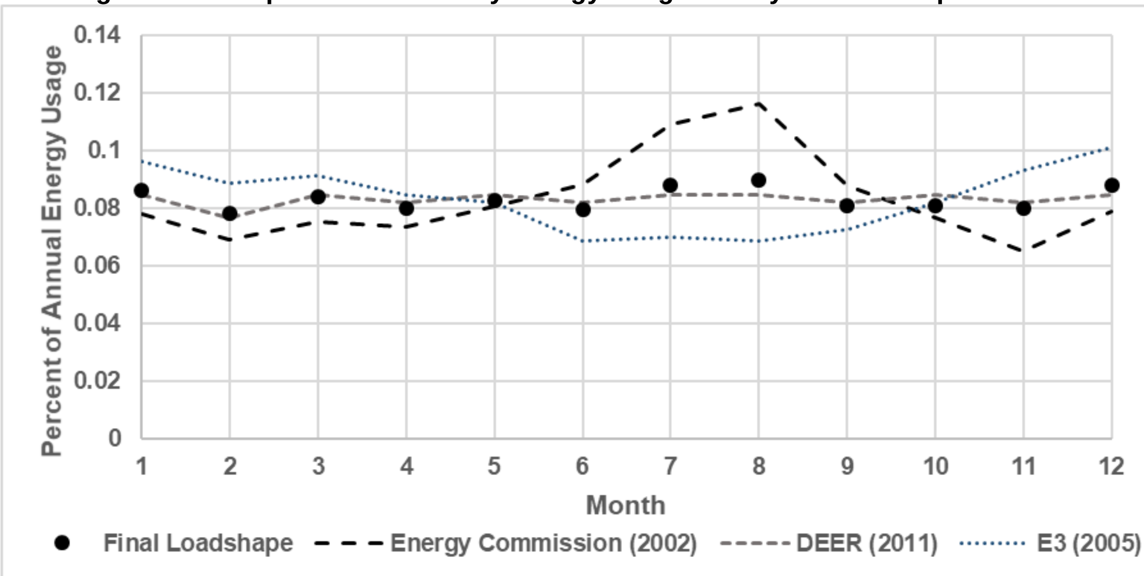
Dryer

ADM reviewed three sources for the dryer end-use: the Energy Commission's existing load shape, as updated in 2002; the EPRI Load Shape Library 4.0 (2016); and the E3 Energy Efficiency Calculator (2005).

Figure 22 through

Figure 30 present the monthly energy use and seasonal weekday/weekend daily profiles for sources and the aggregated load shape. In general, the average daily load shapes appeared consistent with one another regardless of the season. Although the monthly energy use differed from one another, an argument could not be made as to why one profile may be more valid than the other, therefore, ADM averaged all profiles together to create the final load shape.

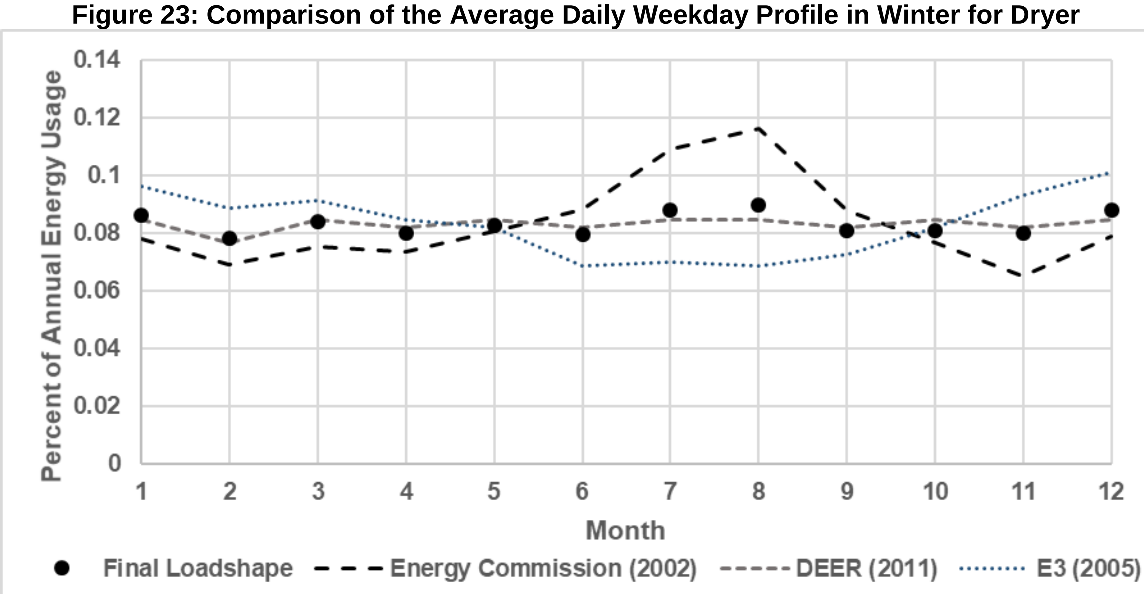
Figure 22: Comparison of Monthly Energy Usage for Dryer Load Shape Sources



A comparison of the monthly energy usage for the dryer end-use as predicted by the Energy Commission's 2002 load shape, EPRI (2016) load shape, and the E3 Energy Efficiency Calculator (2005) load shape.

Source: ADM Associates, Inc.

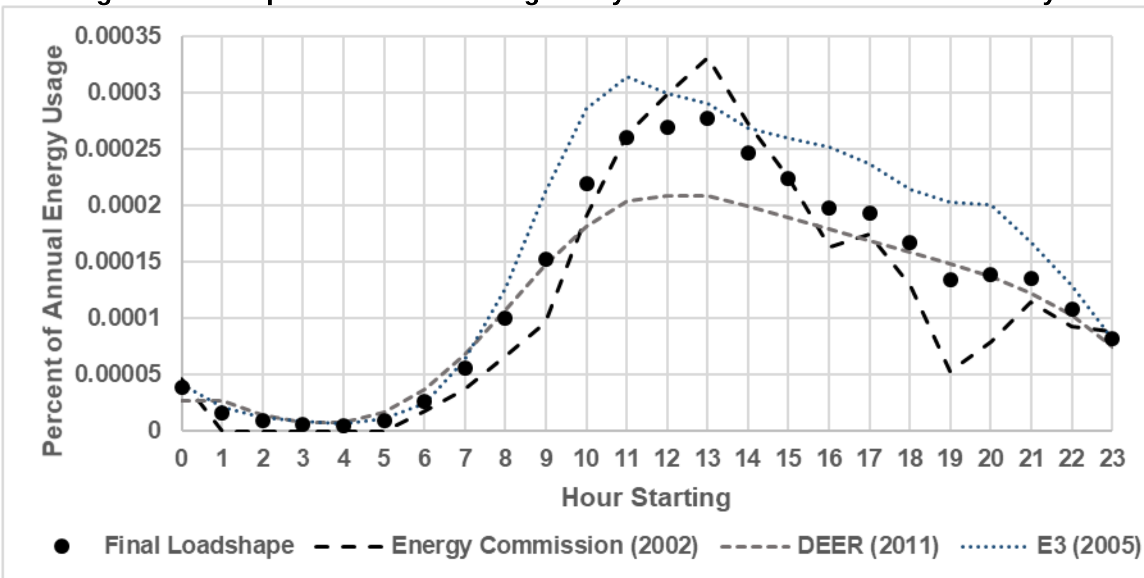
Figure 23: Comparison of the Average Daily Weekday Profile in Winter for Dryer



A comparison of the average daily load shape in weekdays in winter for the dryer end-use as predicted by the Energy Commission's 2002 load shape, EPRI (2016) load shape, and the E3 Energy Efficiency Calculator (2005) load shape.

Source: ADM Associates, Inc.

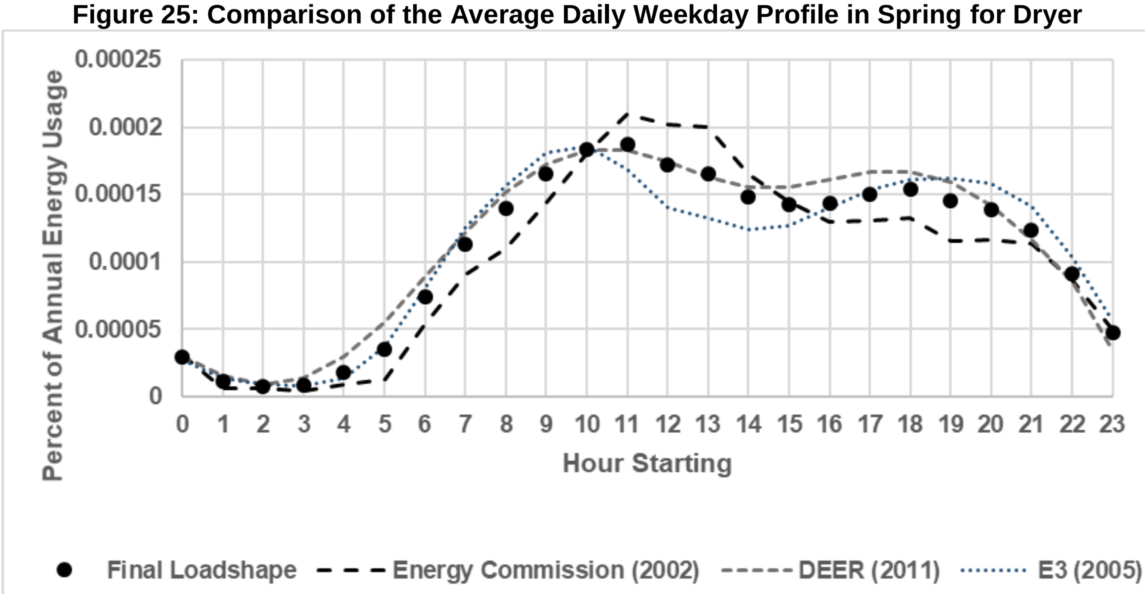
Figure 24: Comparison of the Average Daily Weekend Profile in Winter for Dryer



A comparison of the average daily load shape in weekends in winter for the dryer end-use as predicted by the Energy Commission's 2002 load shape, EPRI (2016) load shape, and the E3 Energy Efficiency Calculator (2005) load shape.

Source: ADM Associates, Inc.

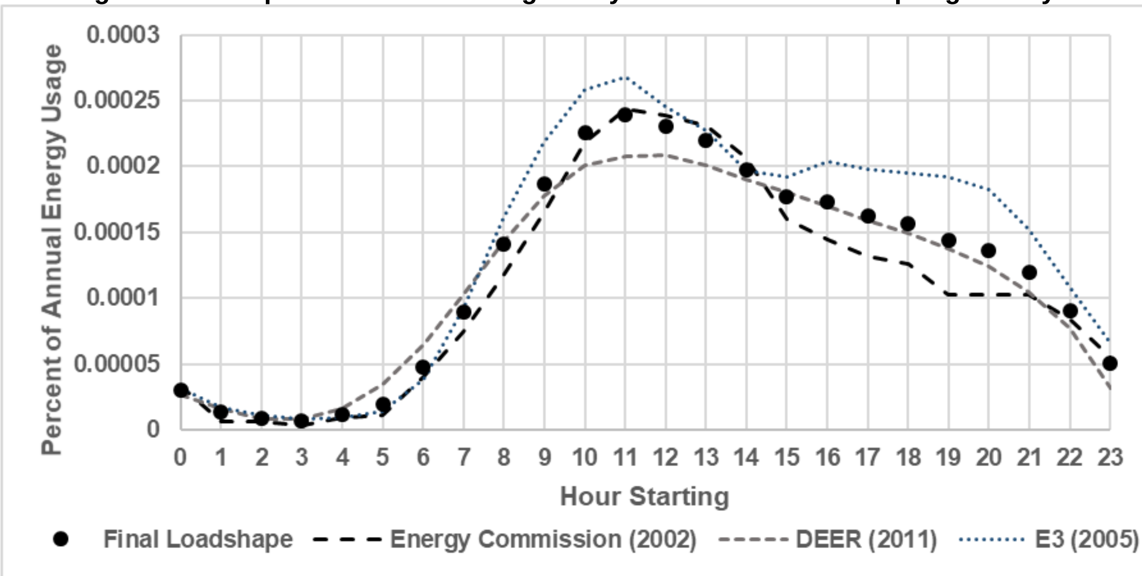
Figure 25: Comparison of the Average Daily Weekday Profile in Spring for Dryer



A comparison of the average daily load shape in weekdays in spring for the dryer end-use as predicted by the Energy Commission's 2002 load shape, EPRI (2016) load shape, and the E3 Energy Efficiency Calculator (2005) load shape.

Source: ADM Associates, Inc.

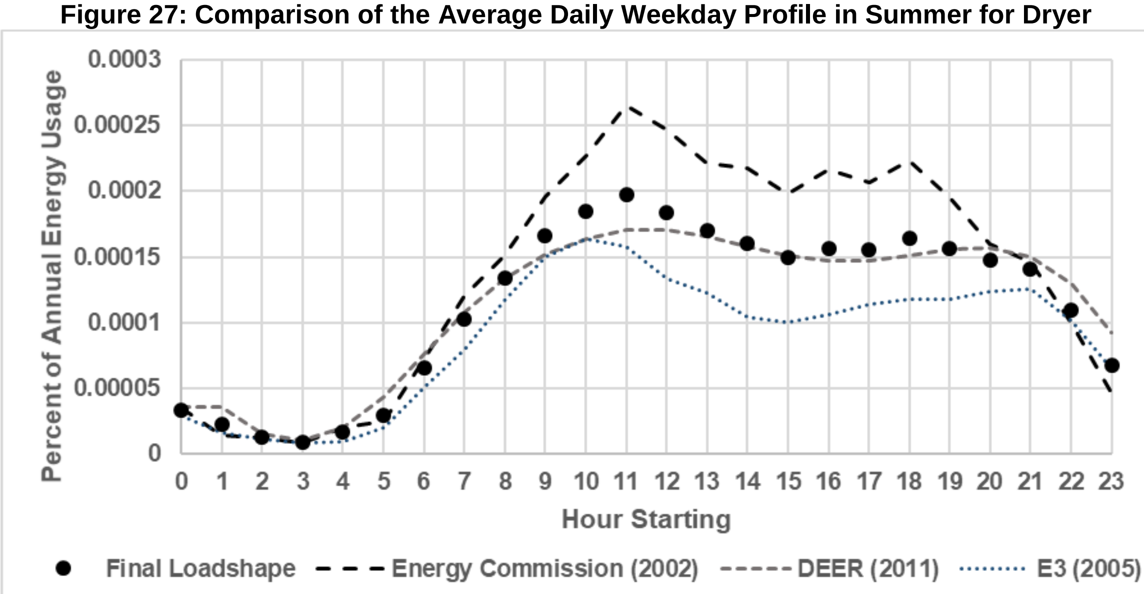
Figure 26: Comparison of the Average Daily Weekend Profile in Spring for Dryer



A comparison of the average daily load shape in weekends in spring for the dryer end-use as predicted by the Energy Commission's 2002 load shape, EPRI (2016) load shape, and the E3 Energy Efficiency Calculator (2005) load shape.

Source: ADM Associates, Inc.

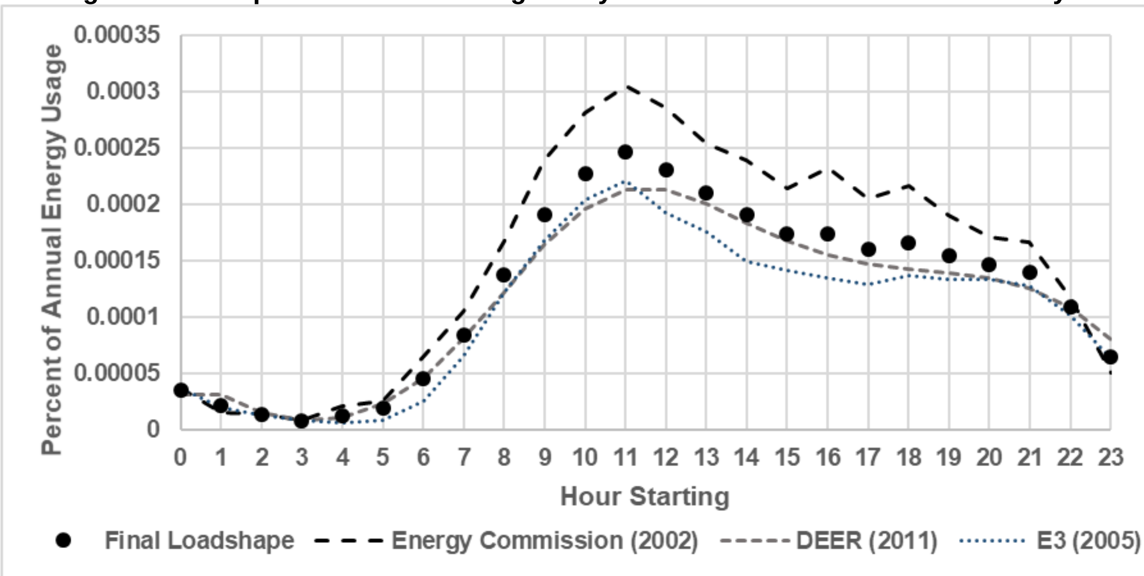
Figure 27: Comparison of the Average Daily Weekday Profile in Summer for Dryer



A comparison of the average daily load shape in weekdays in summer for the dryer end-use as predicted by the Energy Commission's 2002 load shape, EPRI (2016) load shape, and the E3 Energy Efficiency Calculator (2005) load shape.

Source: ADM Associates, Inc.

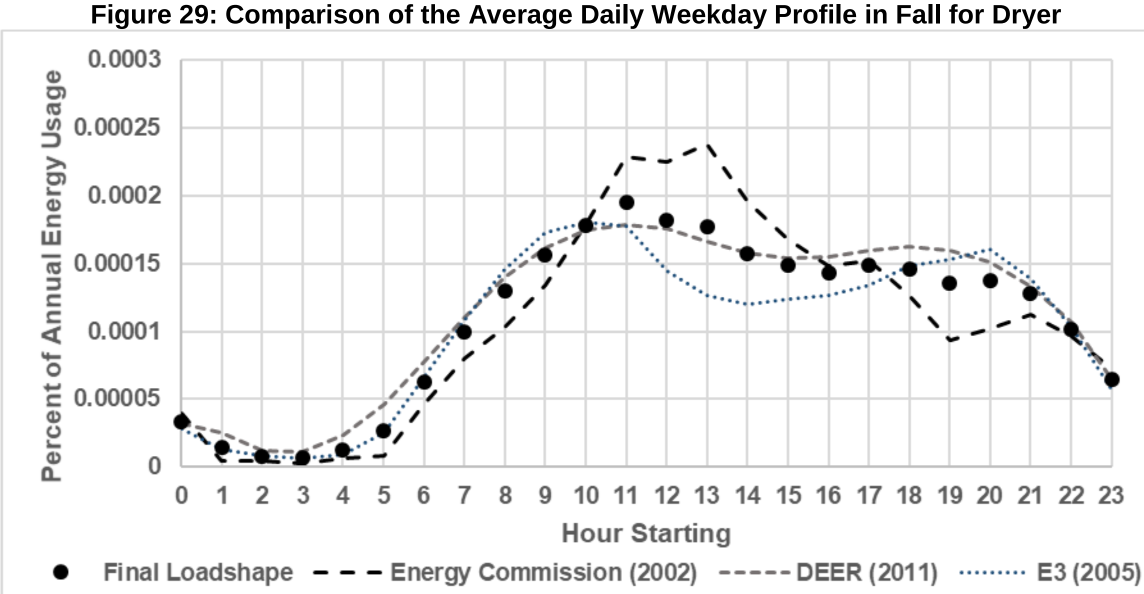
Figure 28: Comparison of the Average Daily Weekend Profile in Summer for Dryer



A comparison of the average daily load shape in weekends in summer for the dryer end-use as predicted by the Energy Commission's 2002 load shape, EPRI (2016) load shape, and the E3 Energy Efficiency Calculator (2005) load shape.

Source: ADM Associates, Inc.

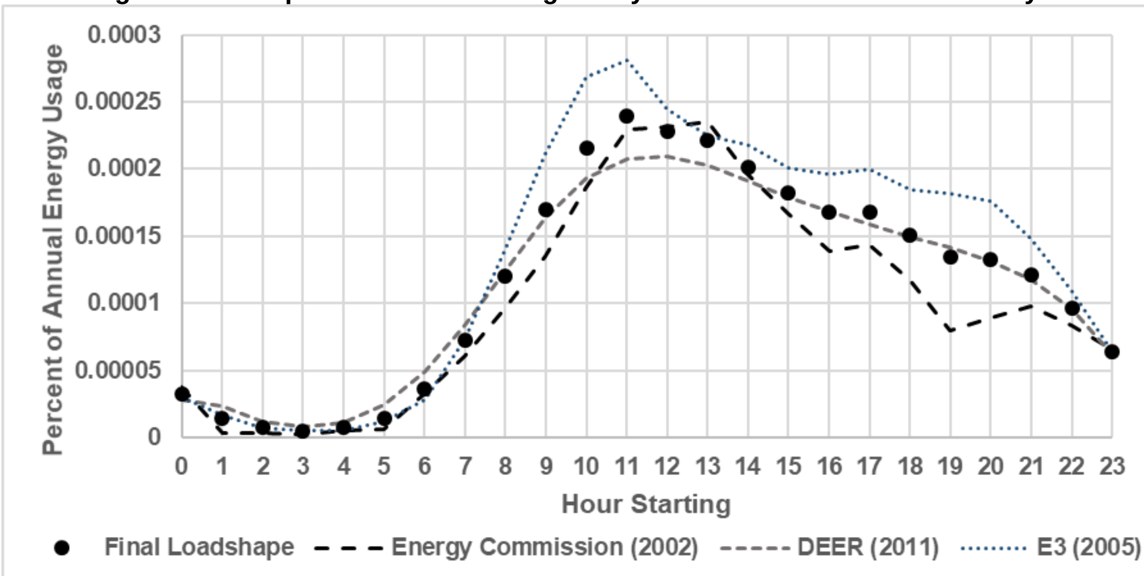
Figure 29: Comparison of the Average Daily Weekday Profile in Fall for Dryer



A comparison of the average daily load shape in weekdays in fall for the dryer end-use as predicted by the Energy Commission's 2002 load shape, EPRI (2016) load shape, and the E3 Energy Efficiency Calculator (2005) load shape.

Source: ADM Associates, Inc.

Figure 30: Comparison of the Average Daily Weekend Profile in Fall for Dryer



A comparison of the average daily load shape in weekends in fall for the dryer end-use as predicted by the Energy Commission's 2002 load shape, EPRI (2016) load shape, and the E3 Energy Efficiency Calculator (2005) load shape.

Source: ADM Associates, Inc.

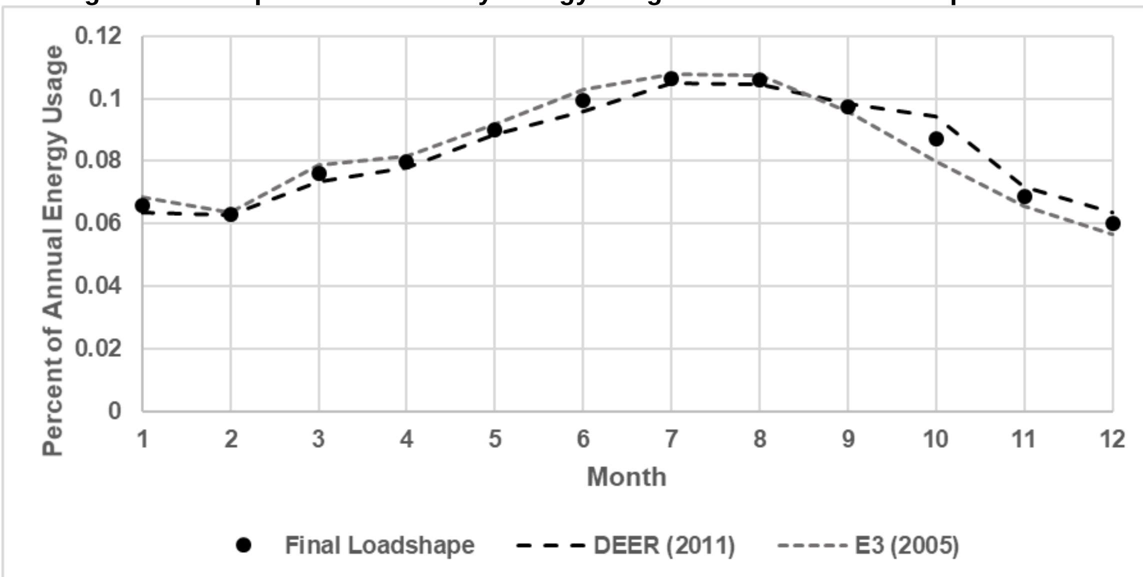
Freezer

ADM reviewed two sources for the freezer end-use: the DEER (2011) and the E3 Energy Efficiency Calculator (2005).

Figure 31 through

Figure 39 present the monthly energy usage and seasonal weekday/weekend daily profiles for both sources and the aggregated load shape. In general, there was good correlation, r=0.82, between both sources, therefore, ADM averaged all profiles together to create the final load shape.

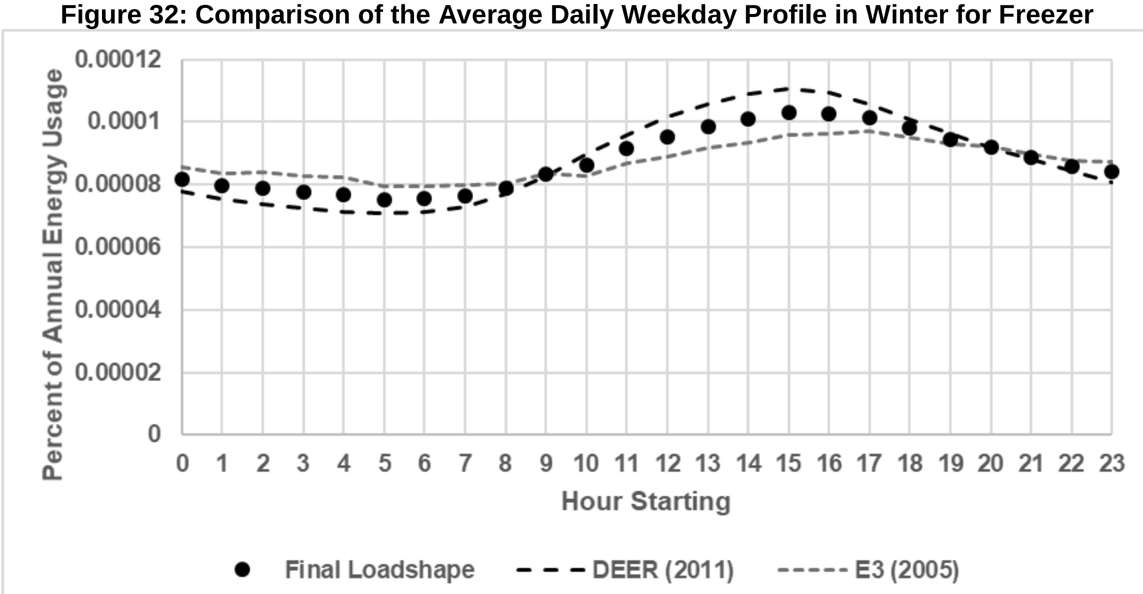
Figure 31: Comparison of Monthly Energy Usage for Freezer Load Shape Sources



A comparison of the monthly energy usage for the freezer end-use as predicted by the DEER (Itron, Inc. 2011) and the E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

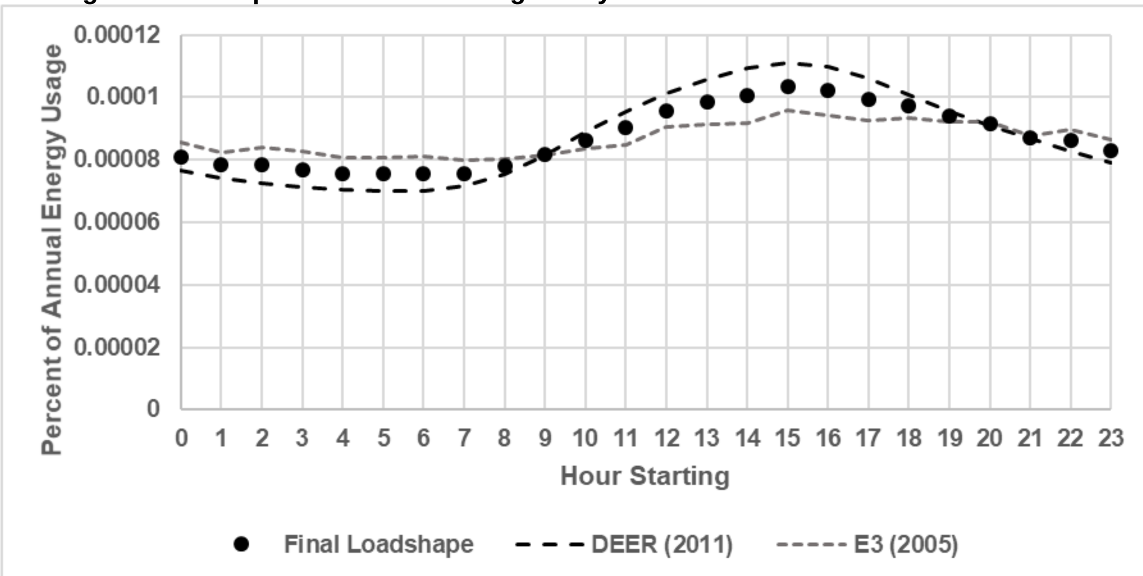
Figure 32: Comparison of the Average Daily Weekday Profile in Winter for Freezer



A comparison of the average daily load shape in weekdays in winter for the freezer end-use as predicted by the DEER (Itron, Inc. 2011) and the E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

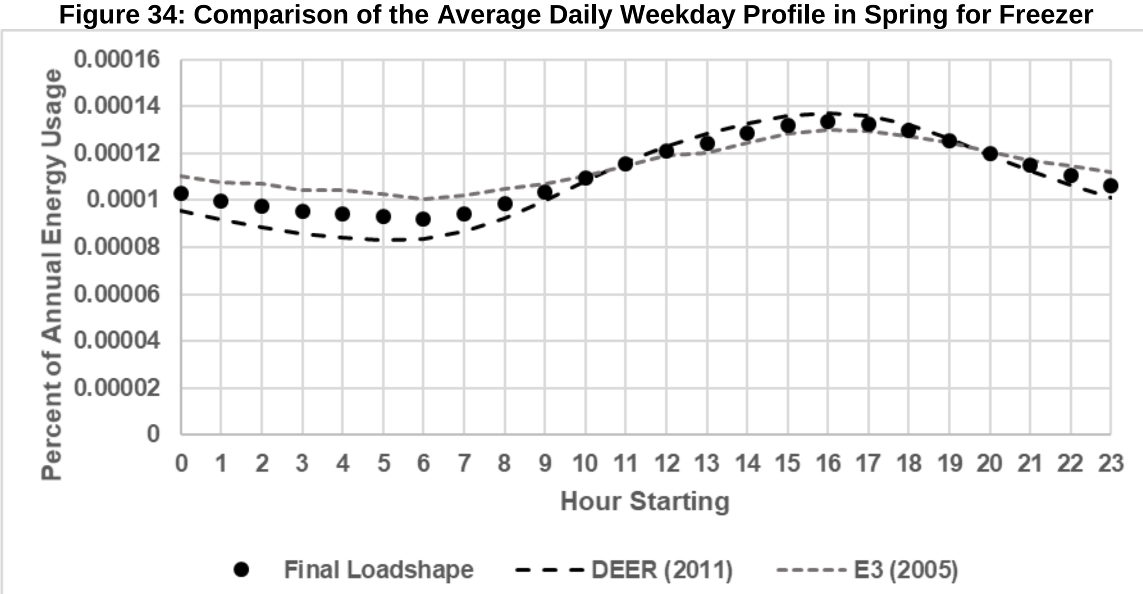
Figure 33: Comparison of the Average Daily Weekend Profile in Winter for Freezer



A comparison of the average daily load shape in weekends in winter for the freezer end-use as predicted by the DEER (Itron, Inc. 2011) and the E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

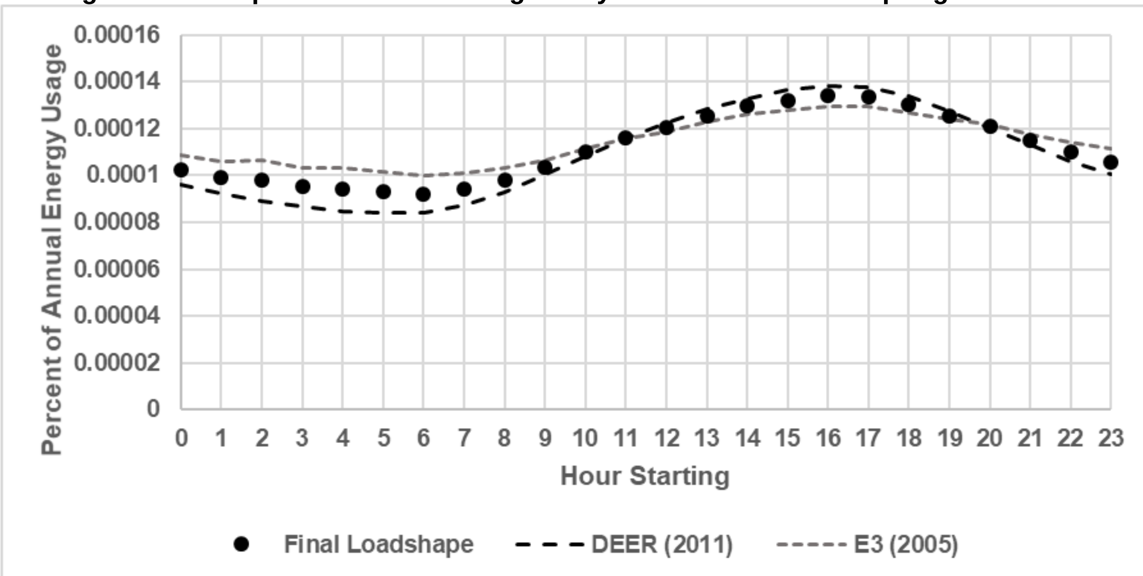
Figure 34: Comparison of the Average Daily Weekday Profile in Spring for Freezer



A comparison of the average daily load shape in weekdays in spring for the freezer end-use as predicted by the DEER (Itron, Inc. 2011) and the E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

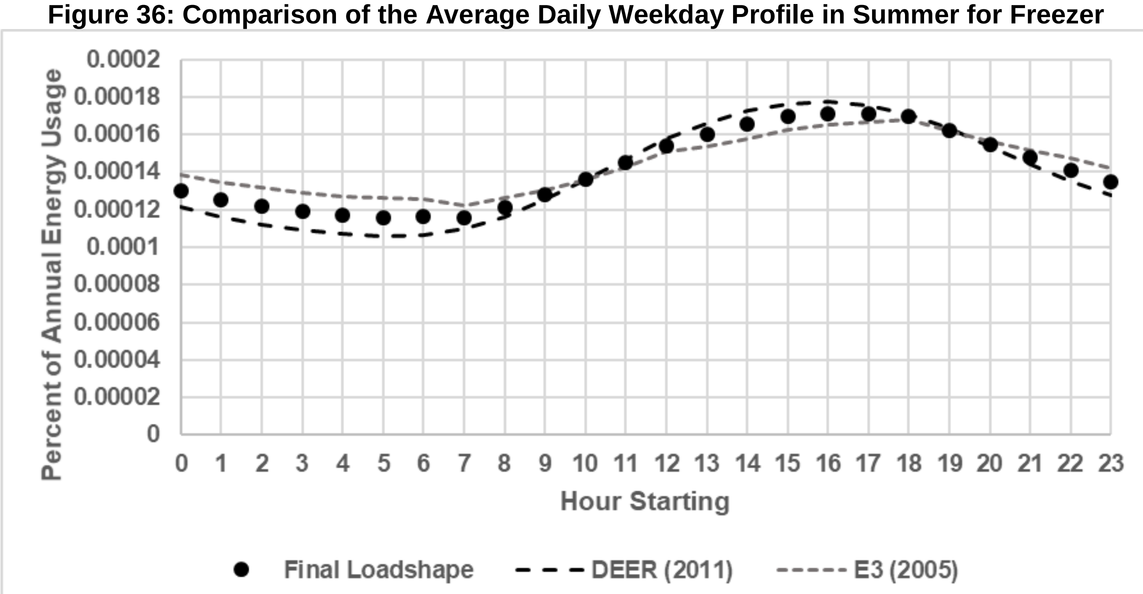
Figure 35: Comparison of the Average Daily Weekend Profile in Spring for Freezer



A comparison of the average daily load shape in weekends in spring for the freezer end-use as predicted by the DEER (Itron, Inc. 2011) and the E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

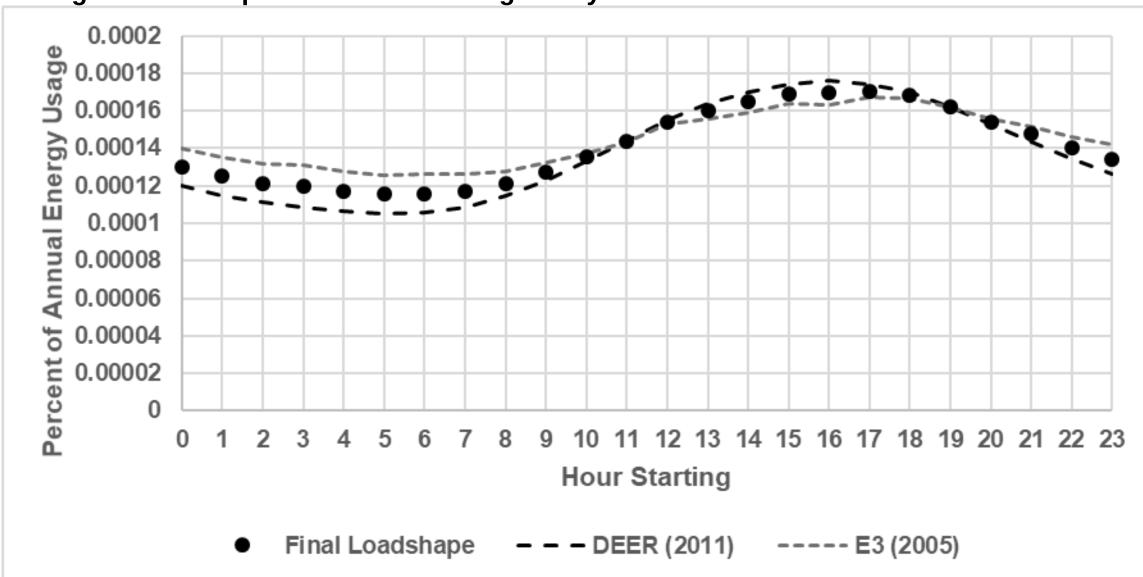
Figure 36: Comparison of the Average Daily Weekday Profile in Summer for Freezer



A comparison of the average daily load shape in weekdays in summer for the freezer end-use as predicted by the DEER (Itron, Inc. 2011) and the E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

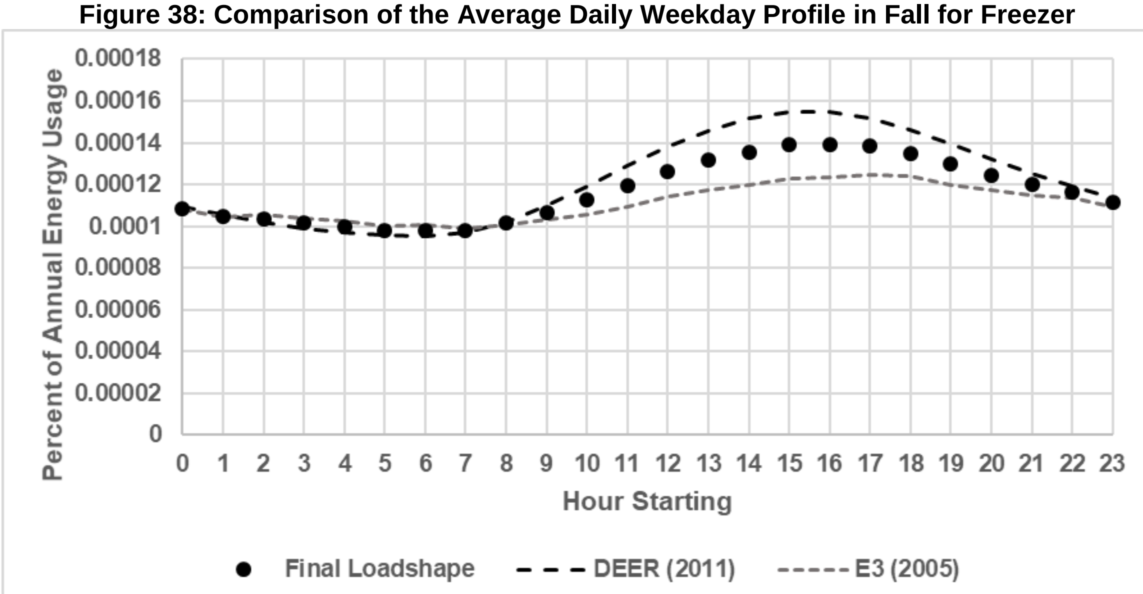
Figure 37: Comparison of the Average Daily Weekend Profile in Summer for Freezer



A comparison of the average daily load shape in weekends in summer for the freezer end-use as predicted by the DEER (Itron, Inc. 2011) and the E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

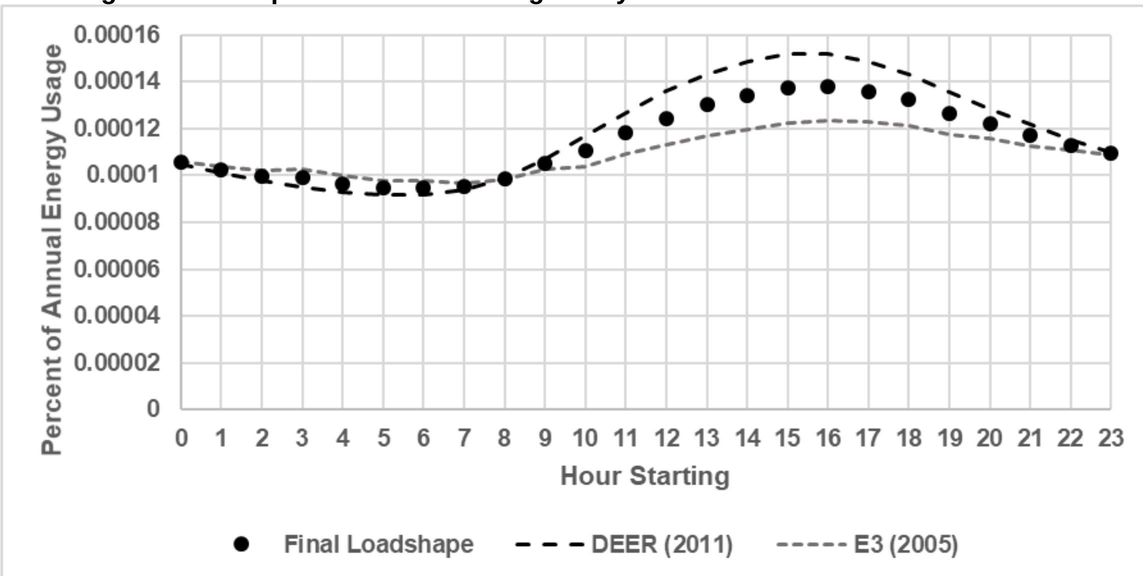
Figure 38: Comparison of the Average Daily Weekday Profile in Fall for Freezer



A comparison of the average daily load shape in weekdays in fall for the Freezer end-use as predicted by the DEER (Itron, Inc. 2011) and the E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

Figure 39: Comparison of the Average Daily Weekend Profile in Fall for Freezer



A comparison of the average daily load shape in weekends in fall for the Freezer end-use as predicted by the DEER (Itron, Inc. 2011) and the E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

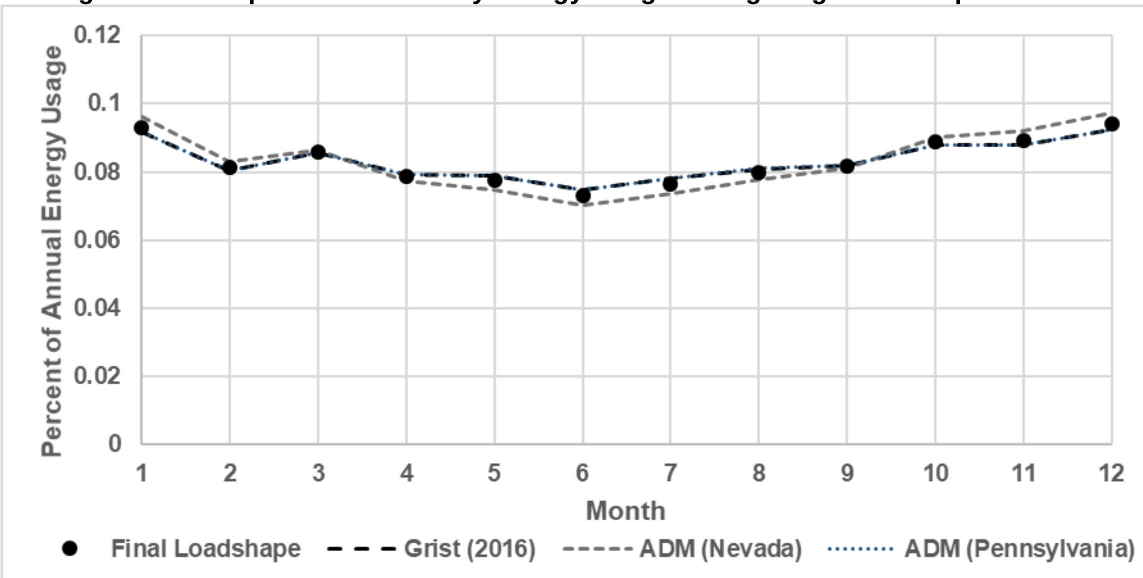
Lighting

ADM reviewed three sources for the lighting end-use: a 2016 lighting study from the Northwest (Grist 2016), and two ADM work papers—one for a client in Nevada in one for a client in Pennsylvania.

Figure 40 through

Figure 48 present the monthly energy usage and seasonal weekday/weekend daily profiles for both sources and the aggregated load shape. In general, there was good correspondence between all sources, $r > 0.87$ for all shapes. Therefore, ADM averaged all profiles together to create the final load shape.

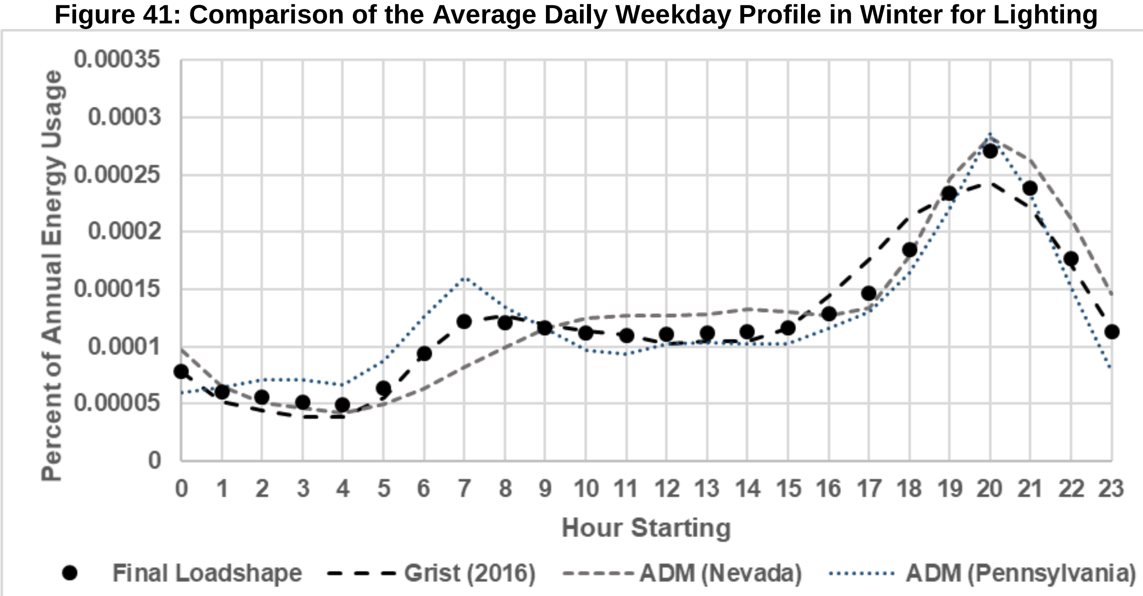
Figure 40: Comparison of Monthly Energy Usage for Lighting Load Shape Sources



A comparison of the monthly energy usage for the lighting end-use as predicted by the 2016 Grist study and the two ADM work papers.

Source: ADM Associates, Inc.

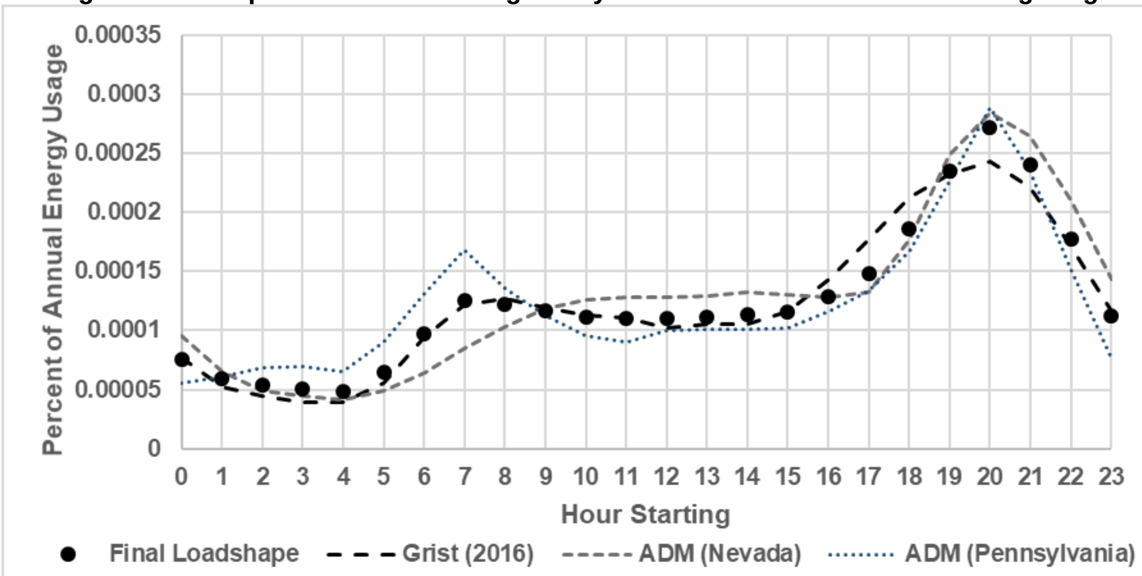
Figure 41: Comparison of the Average Daily Weekday Profile in Winter for Lighting



A comparison of the average daily load shape in weekdays in winter for the lighting end-use as predicted by the 2016 Grist study and the two ADM work papers.

Source: ADM Associates, Inc.

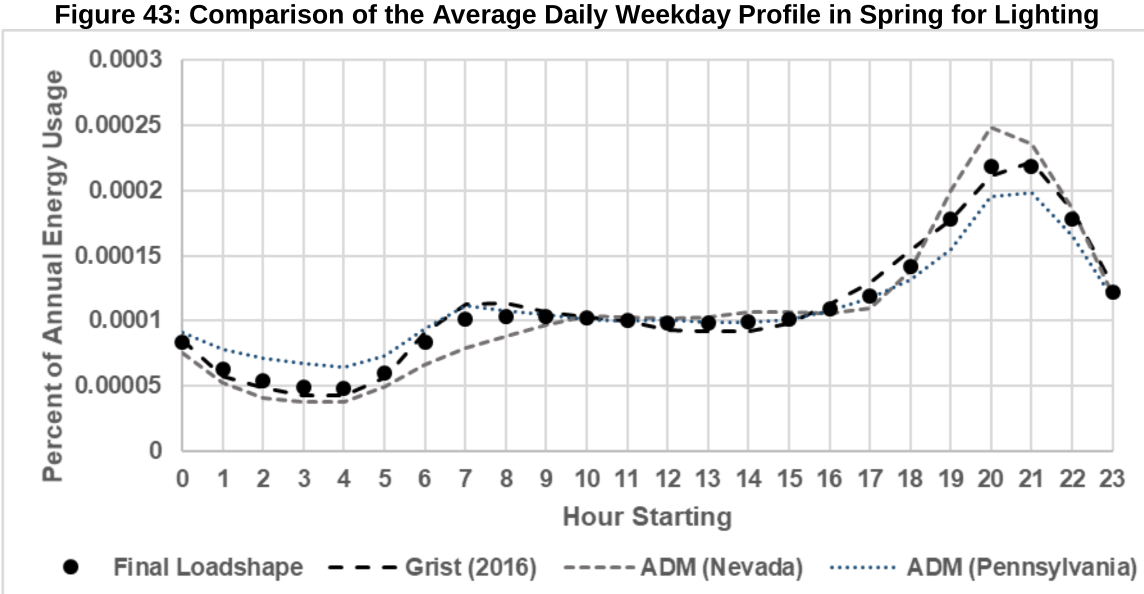
Figure 42: Comparison of the Average Daily Weekend Profile in Winter for Lighting



A comparison of the average daily load shape in weekends in winter for the lighting end-use as predicted by the 2016 Grist study and the two ADM work papers.

Source: ADM Associates, Inc.

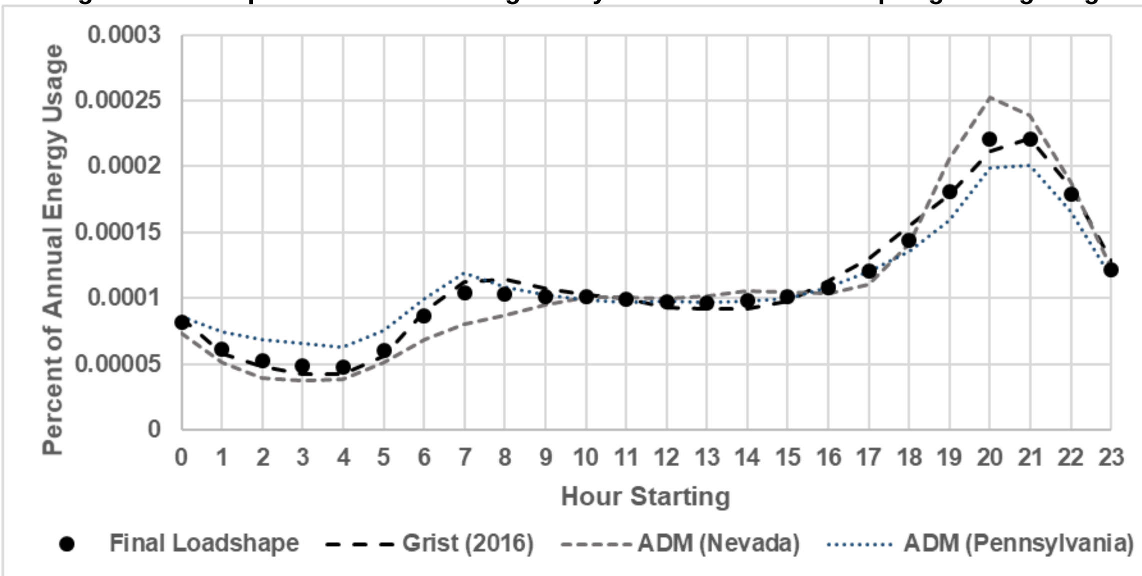
Figure 43: Comparison of the Average Daily Weekday Profile in Spring for Lighting



A comparison of the average daily load shape in weekdays in spring for the lighting end-use as predicted by the 2016 Grist study and the two ADM work papers.

Source: ADM Associates, Inc.

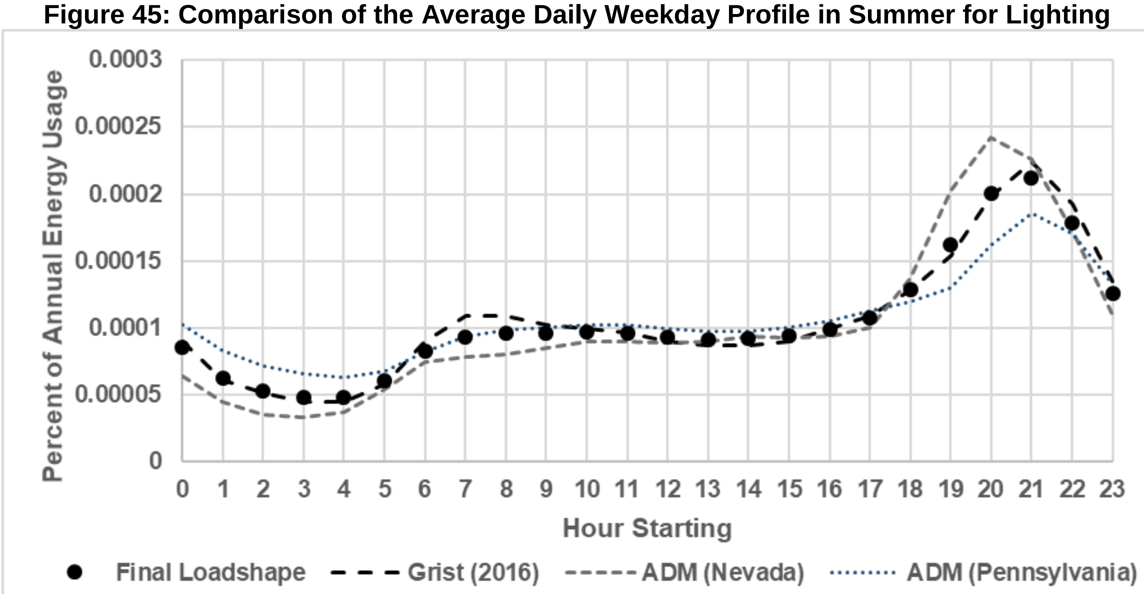
Figure 44: Comparison of the Average Daily Weekend Profile in Spring for Lighting



A comparison of the average daily load shape in weekends in spring for the lighting end-use as predicted by the 2016 Grist study and the two ADM work papers.

Source: ADM Associates, Inc.

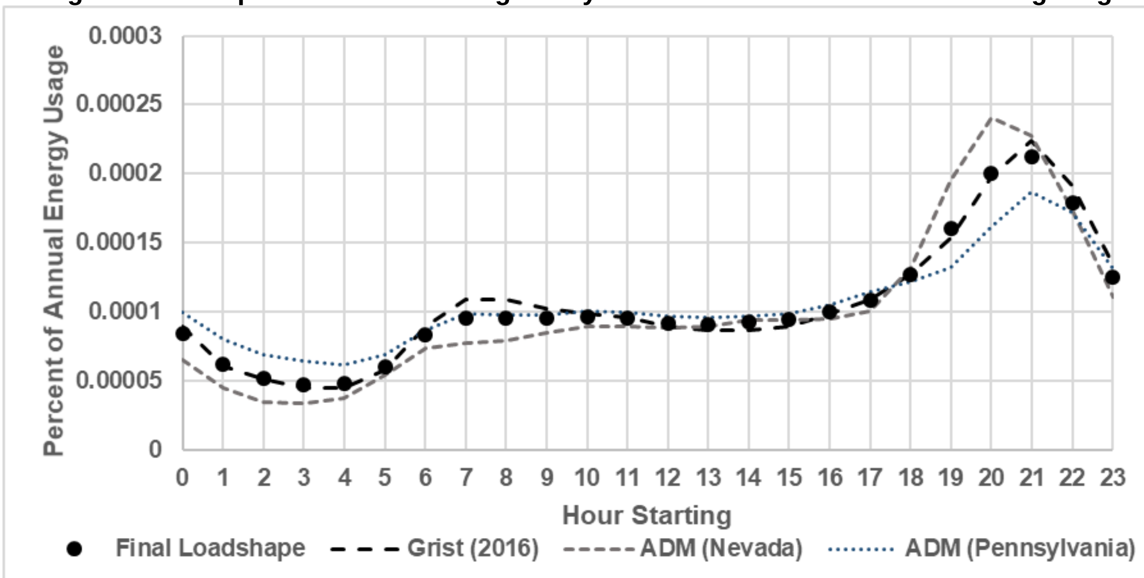
Figure 45: Comparison of the Average Daily Weekday Profile in Summer for Lighting



A comparison of the average daily load shape in weekdays in summer for the lighting end-use as predicted by the 2016 Grist study and the two ADM work papers.

Source: ADM Associates, Inc.

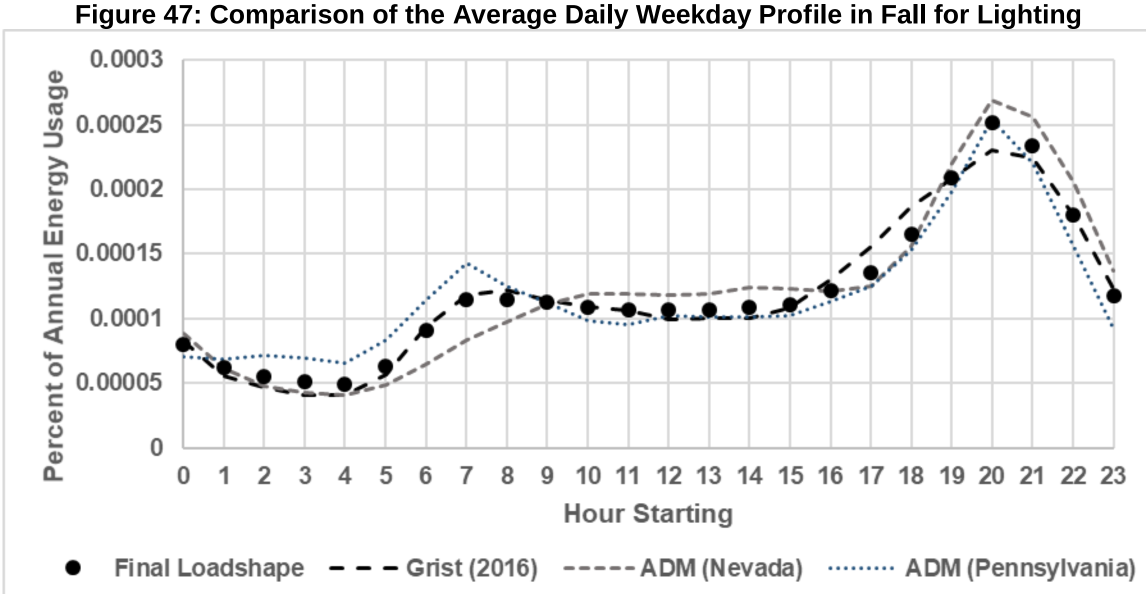
Figure 46: Comparison of the Average Daily Weekend Profile in Summer for Lighting



A comparison of the average daily load shape in weekends in summer for the lighting end-use as predicted by the 2016 Grist study and the two ADM work papers.

Source: ADM Associates, Inc.

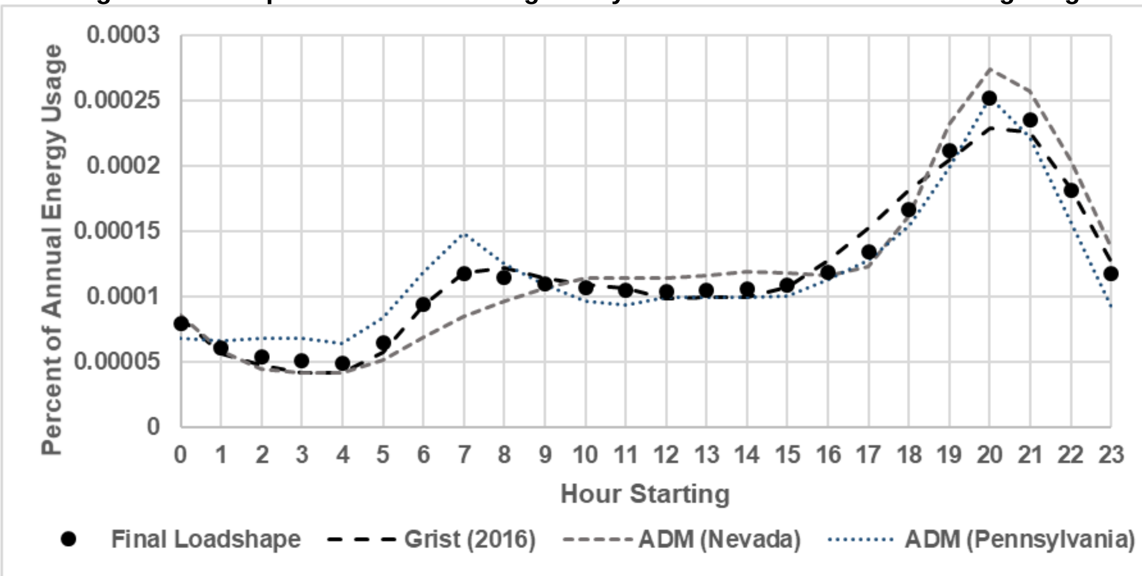
Figure 47: Comparison of the Average Daily Weekday Profile in Fall for Lighting



A comparison of the average daily load shape in weekdays in fall for the lighting end-use as predicted by the 2016 Grist study and the two ADM work papers.

Source: ADM Associates, Inc.

Figure 48: Comparison of the Average Daily Weekend Profile in Fall for Lighting



A comparison of the average daily load shape in weekends in fall for the lighting end-use as predicted by the 2016 Grist study and the two ADM work papers.

Source: ADM Associates, Inc.

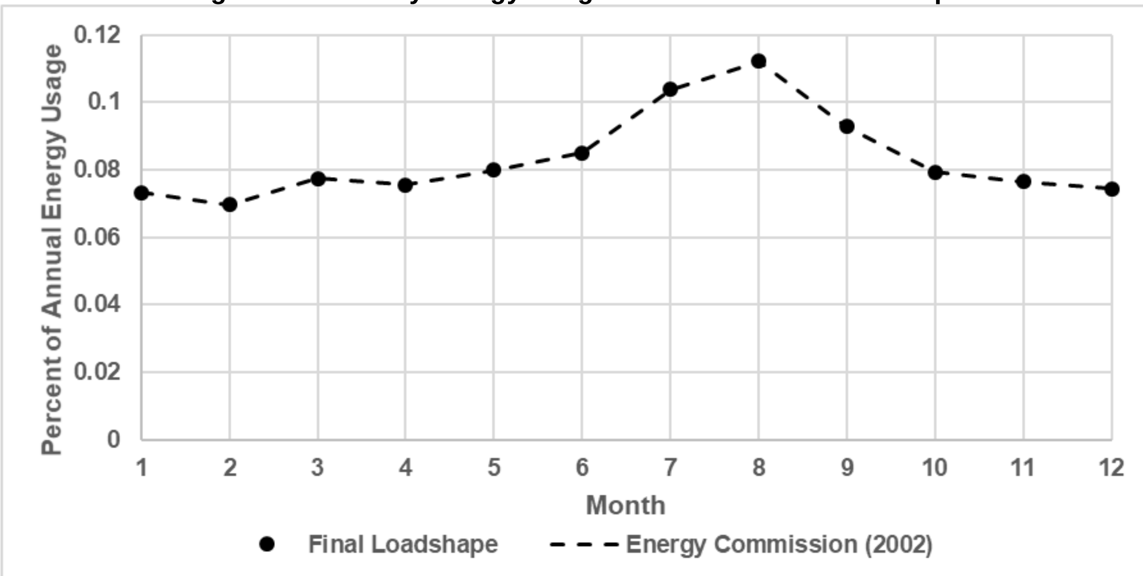
Pool Heater

The amount of resources with an isolated pool heater load shape was limited. Therefore, ADM passed through the Energy Commission's existing load shape as updated in 2002.

Figure 49 through

Figure 57 present the monthly energy use and seasonal weekday/weekend daily profiles for this load shape.

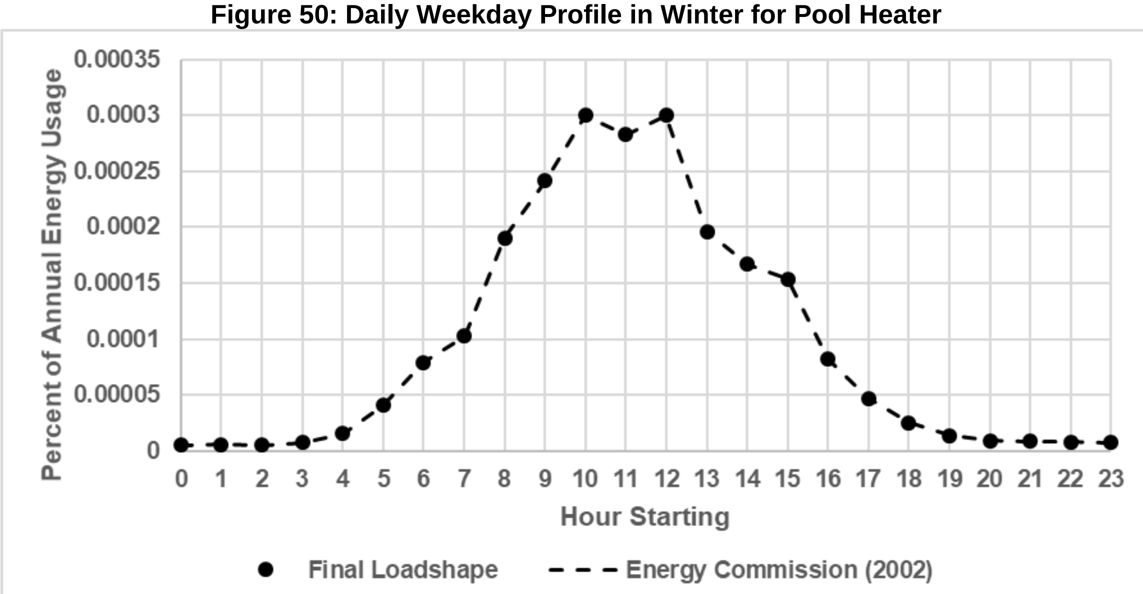
Figure 49: Monthly Energy Usage for Pool Heater Load Shape



A comparison of the monthly energy usage for pool heater as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

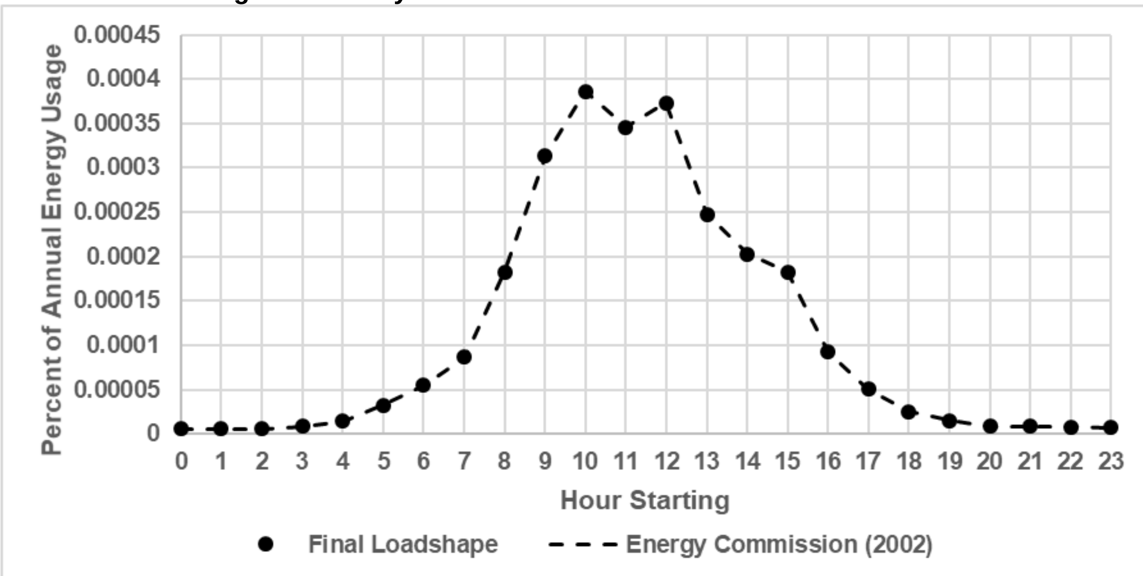
Figure 50: Daily Weekday Profile in Winter for Pool Heater



A comparison of the average daily load shape in weekdays in winter for the pool heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

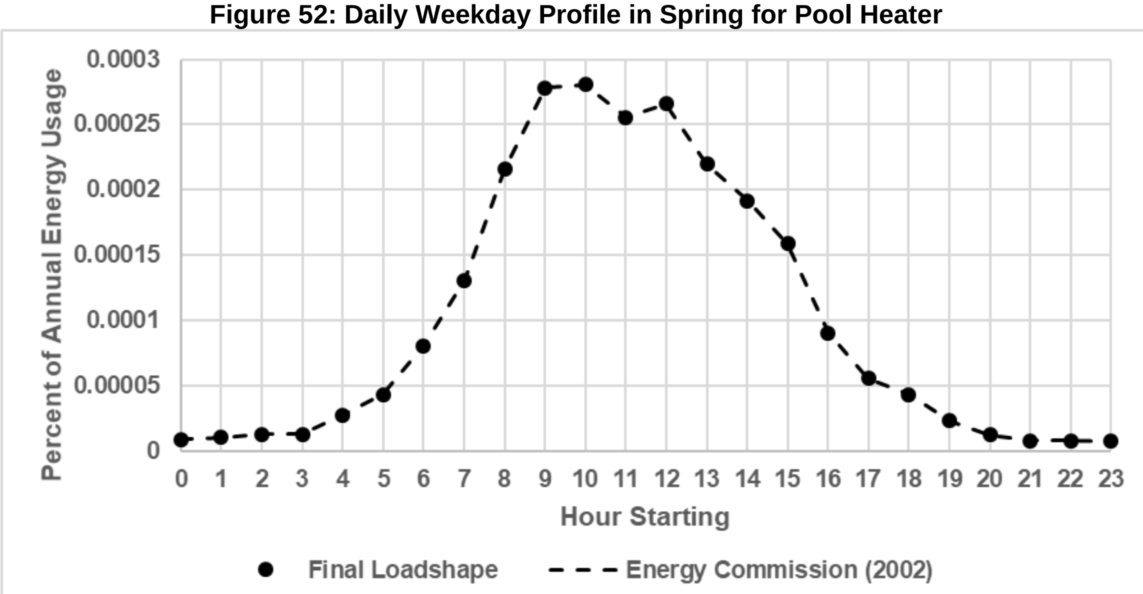
Figure 51: Daily Weekend Profile in Winter for Pool Heater



A comparison of the average daily load shape in weekends in winter for the pool heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

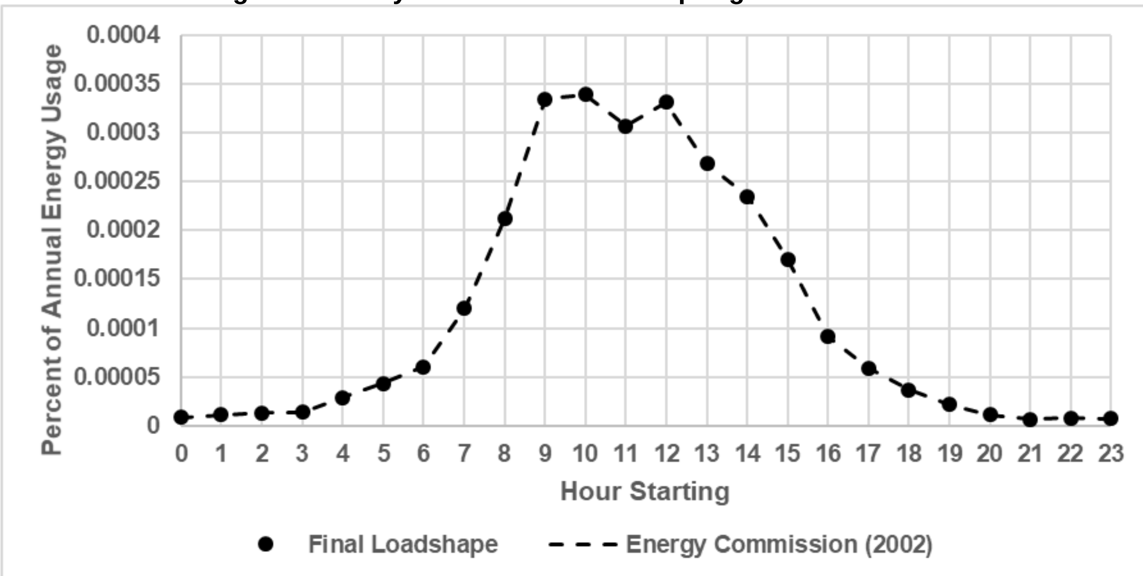
Figure 52: Daily Weekday Profile in Spring for Pool Heater



A comparison of the average daily load shape in weekdays in spring for the pool heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

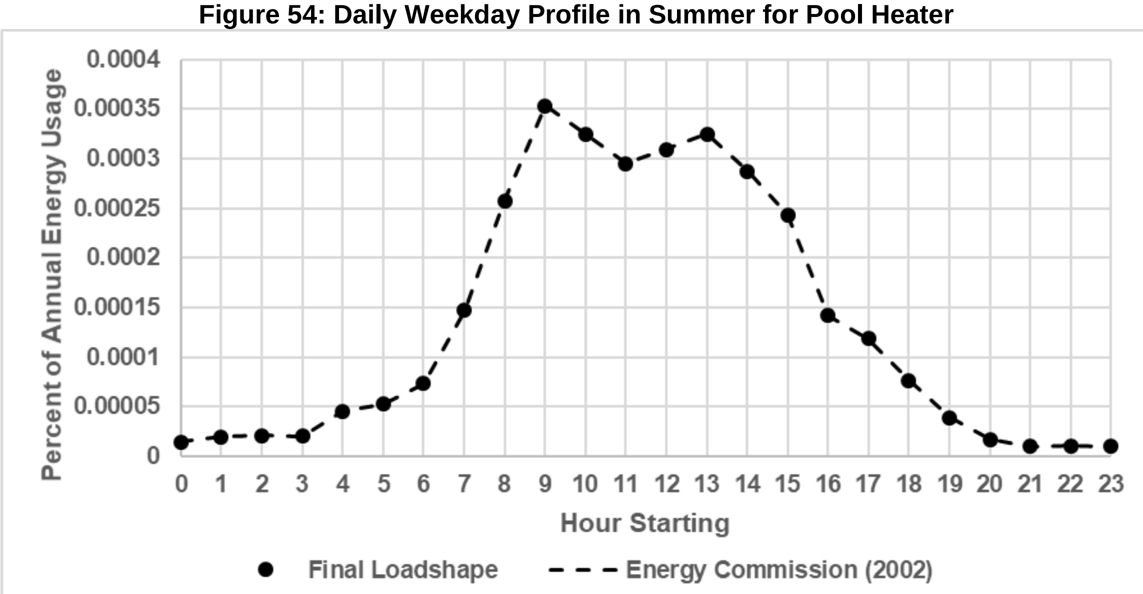
Figure 53: Daily Weekend Profile in Spring for Pool Heater



A comparison of the average daily load shape in weekends in spring for the pool heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

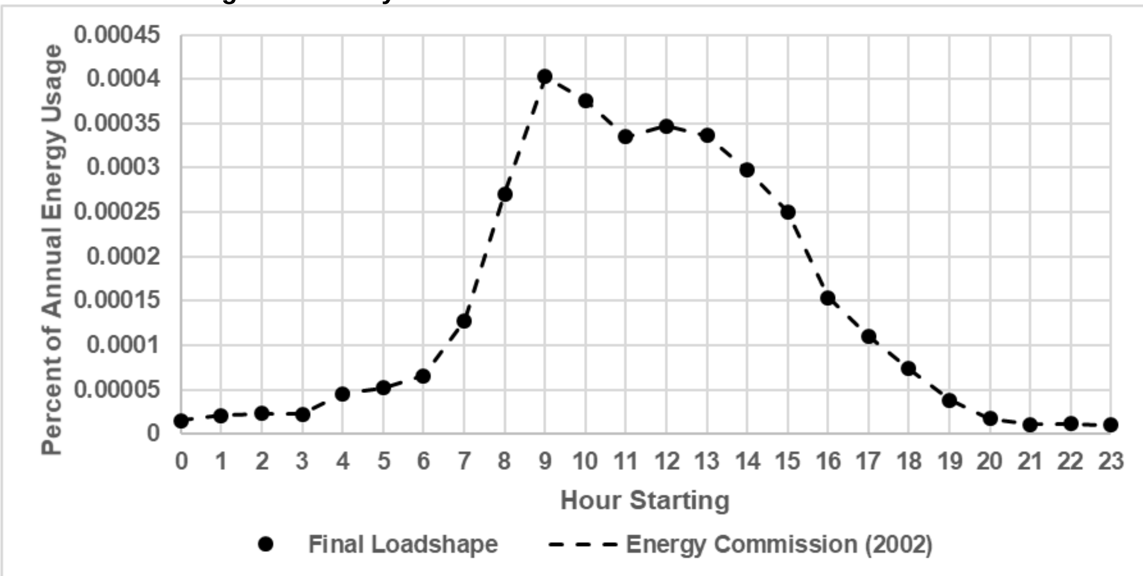
Figure 54: Daily Weekday Profile in Summer for Pool Heater



A comparison of the average daily load shape in weekdays in summer for the pool heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

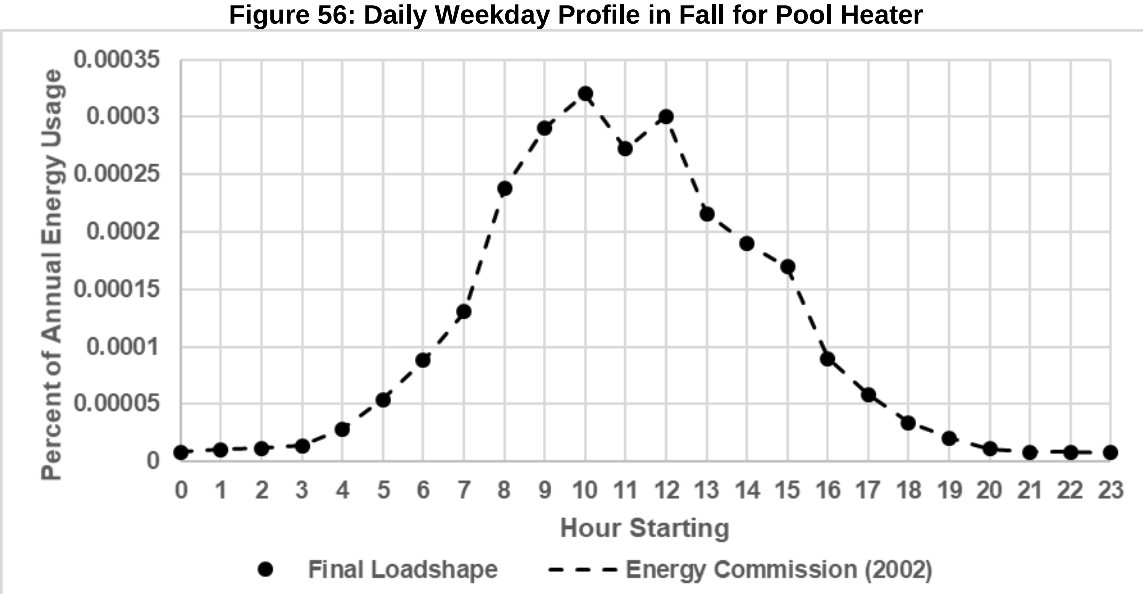
Figure 55: Daily Weekend Profile in Summer for Pool Heater



A comparison of the average daily load shape in weekends in summer for the pool heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

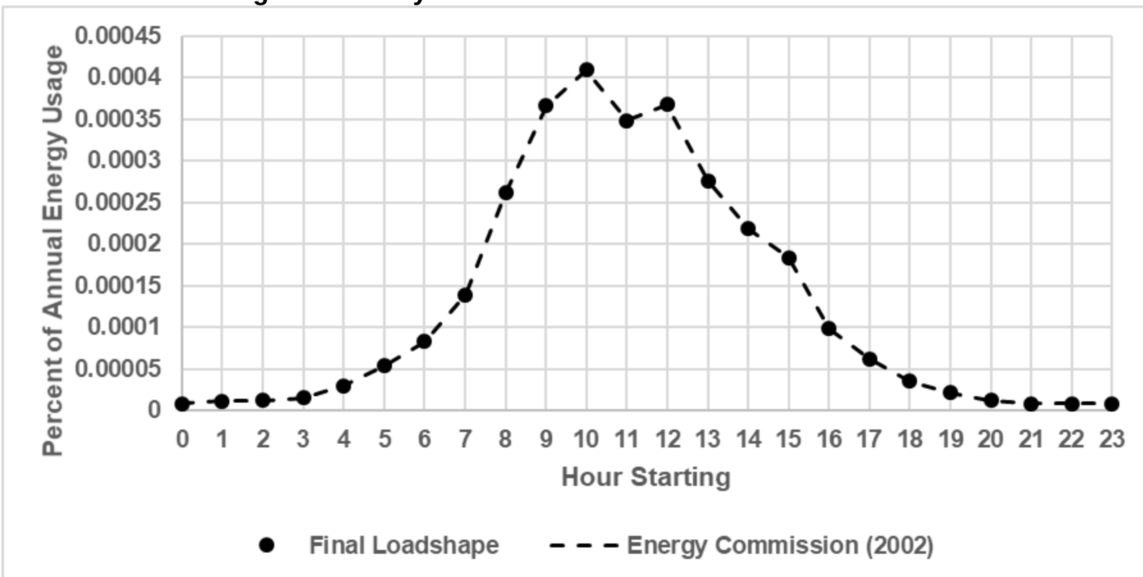
Figure 56: Daily Weekday Profile in Fall for Pool Heater



A comparison of the average daily load shape in weekdays in fall for the pool heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

Figure 57: Daily Weekend Profile in Fall for Pool Heater



A comparison of the average daily load shape in weekends in fall for the pool heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

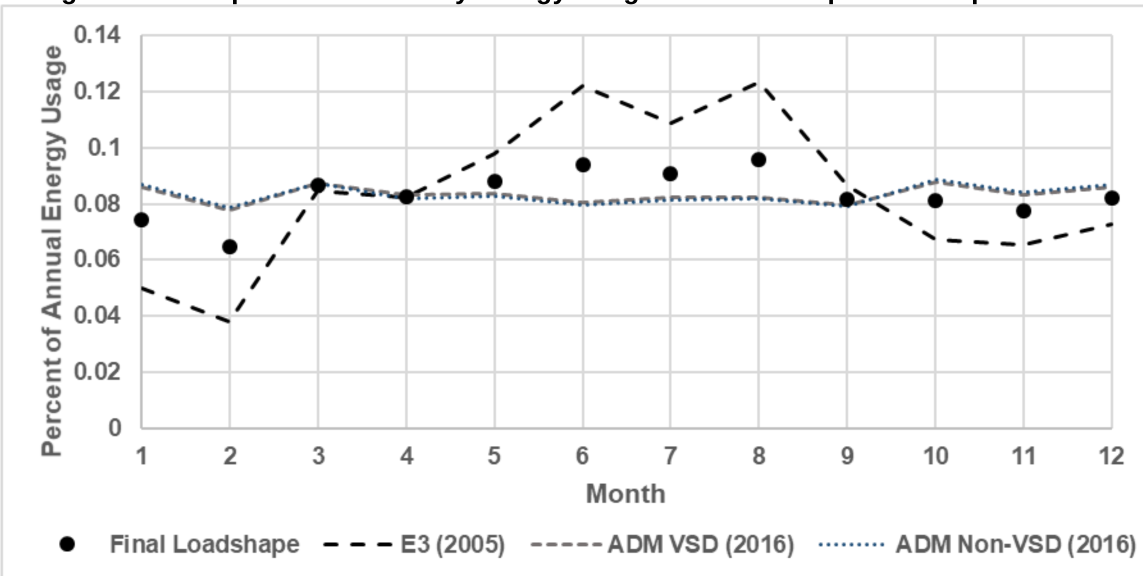
Pool Pump

ADM reviewed two sources for the pool pump end-use: the E3 Energy Efficiency Calculator (2005) and a 2016 ADM study conducted for SMUD, which includes load shapes for VSD pool pumps and non-VSD pool pumps.

Figure 58 through

Figure 66 present these load shapes. Although there was a fair amount of volatility between the two data sources, an argument could not be made as to why one profile may be more valid than the other, therefore, ADM averaged all profiles together to create the final load shape.

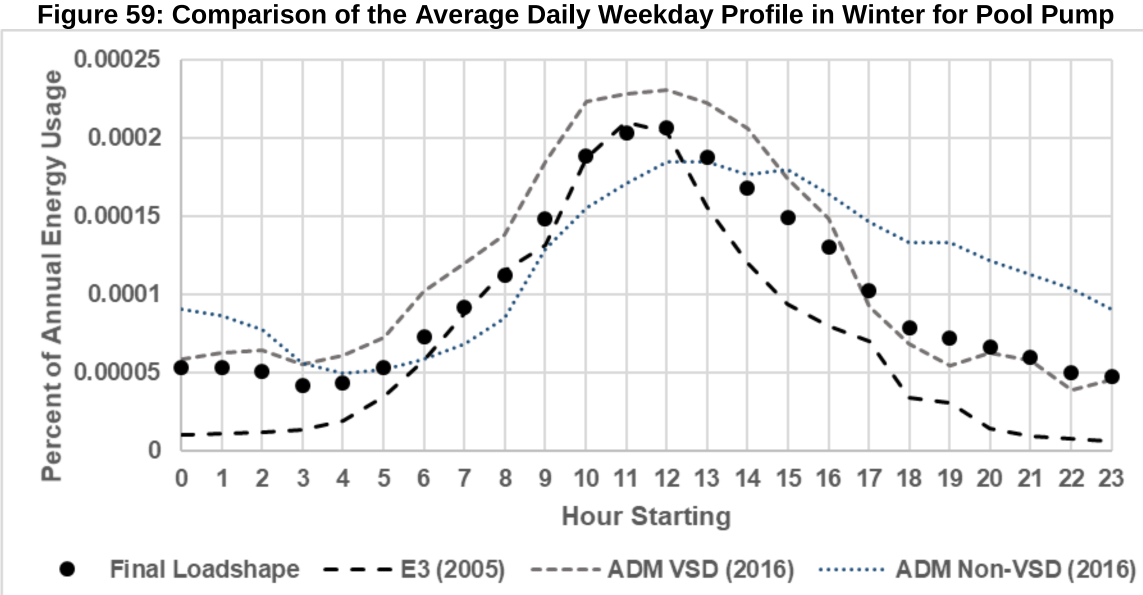
Figure 58: Comparison of Monthly Energy Usage for Pool Pump Load Shape Sources



A comparison of the monthly energy usage for the pool pump end-use as predicted by the 2005 E3 Energy Efficiency Calculator and the 2016 ADM study.

Source: ADM Associates, Inc.

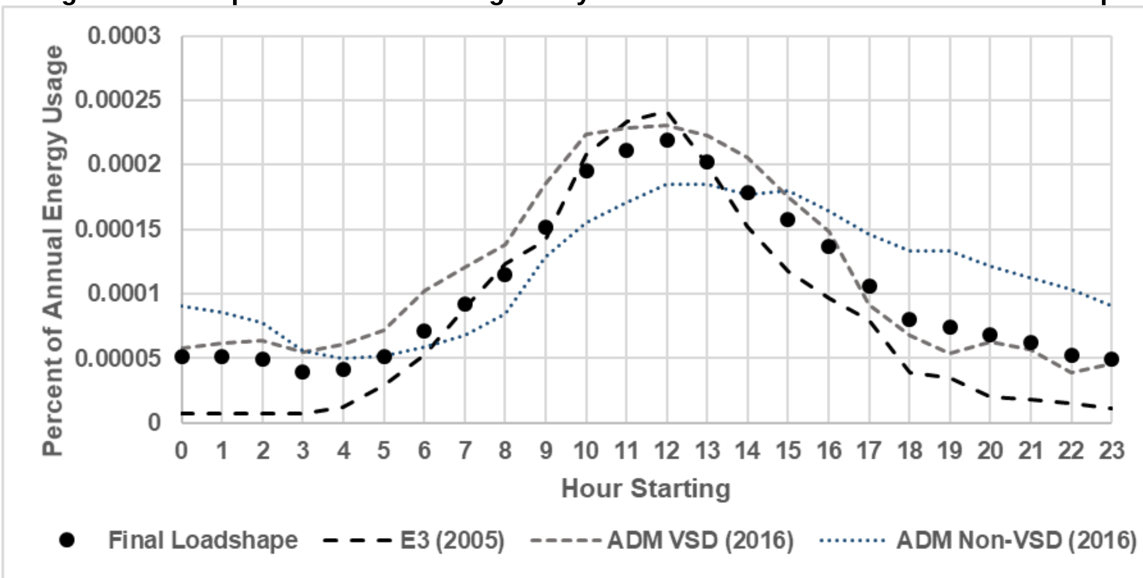
Figure 59: Comparison of the Average Daily Weekday Profile in Winter for Pool Pump



A comparison of the average daily load shape in weekdays in winter for the pool pump end-use as predicted by the 2005 E3 Energy Efficiency Calculator and the 2016 ADM study.

Source: ADM Associates, Inc.

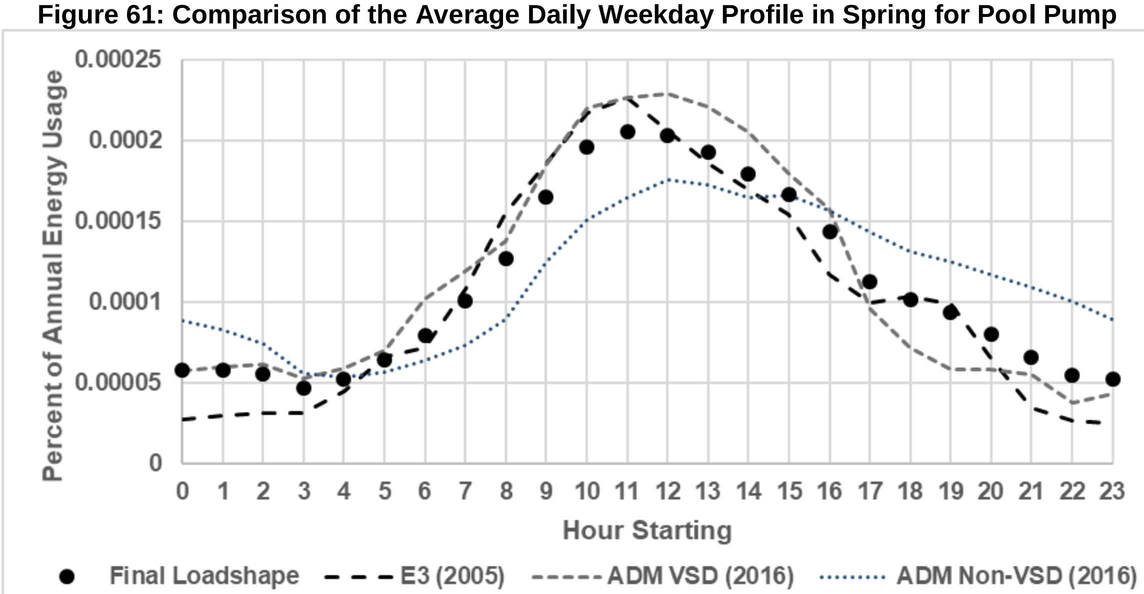
Figure 60: Comparison of the Average Daily Weekend Profile in Winter for Pool Pump



A comparison of the average daily load shape in weekends in winter for the pool pump end-use as predicted by the 2005 E3 Energy Efficiency Calculator and the 2016 ADM study.

Source: ADM Associates, Inc.

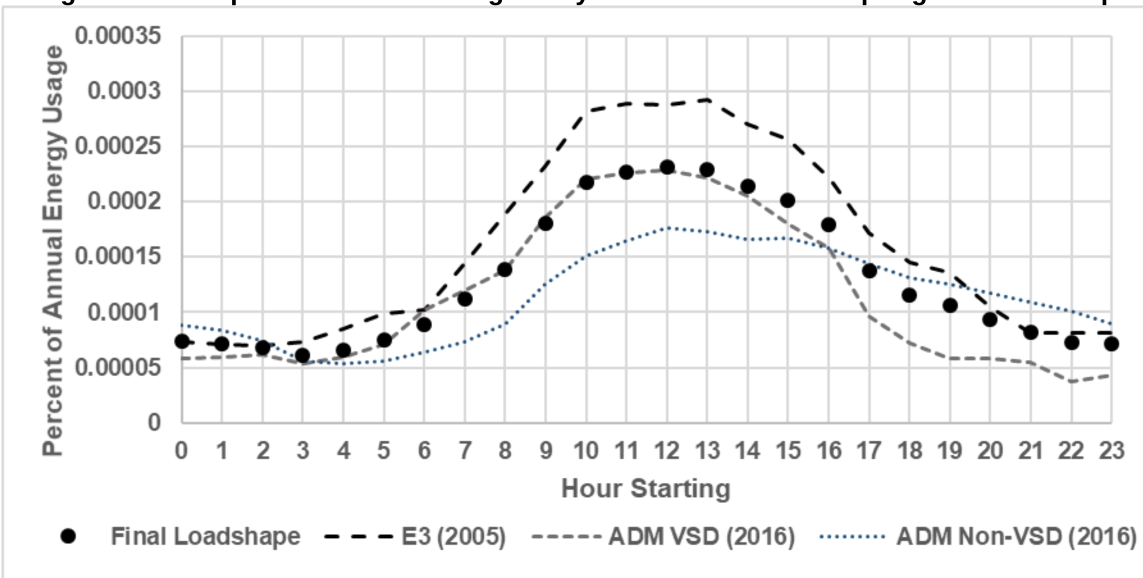
Figure 61: Comparison of the Average Daily Weekday Profile in Spring for Pool Pump



A comparison of the average daily load shape in weekdays in spring for the pool pump end-use as predicted by the 2005 E3 Energy Efficiency Calculator and the 2016 ADM study.

Source: ADM Associates, Inc.

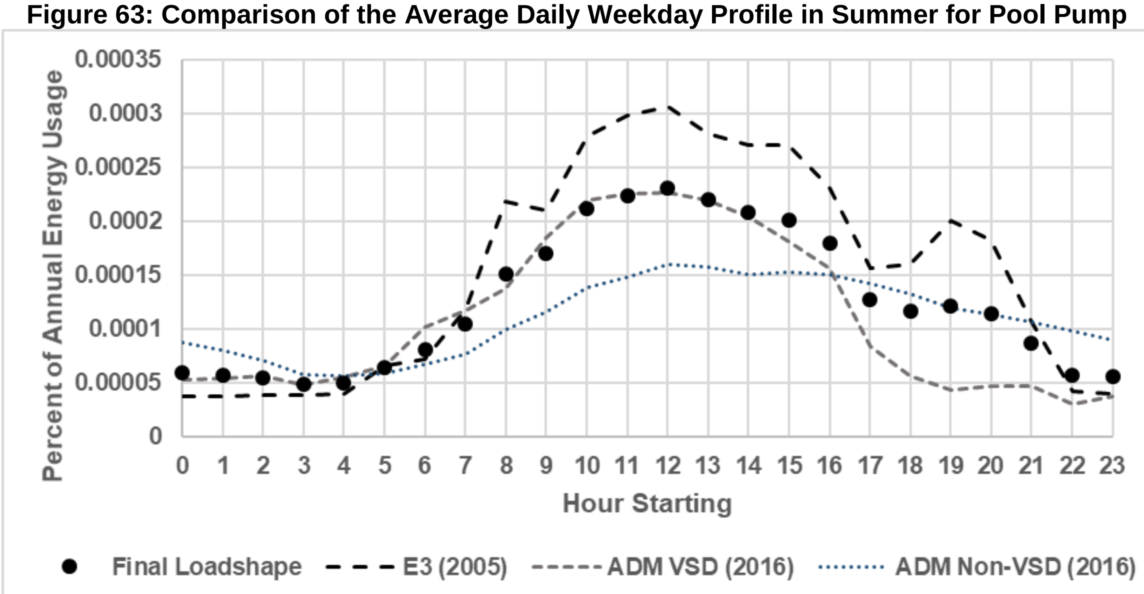
Figure 62: Comparison of the Average Daily Weekend Profile in Spring for Pool Pump



A comparison of the average daily load shape in weekends in spring for the pool pump end-use as predicted by the 2005 E3 Energy Efficiency Calculator and the 2016 ADM study.

Source: ADM Associates, Inc.

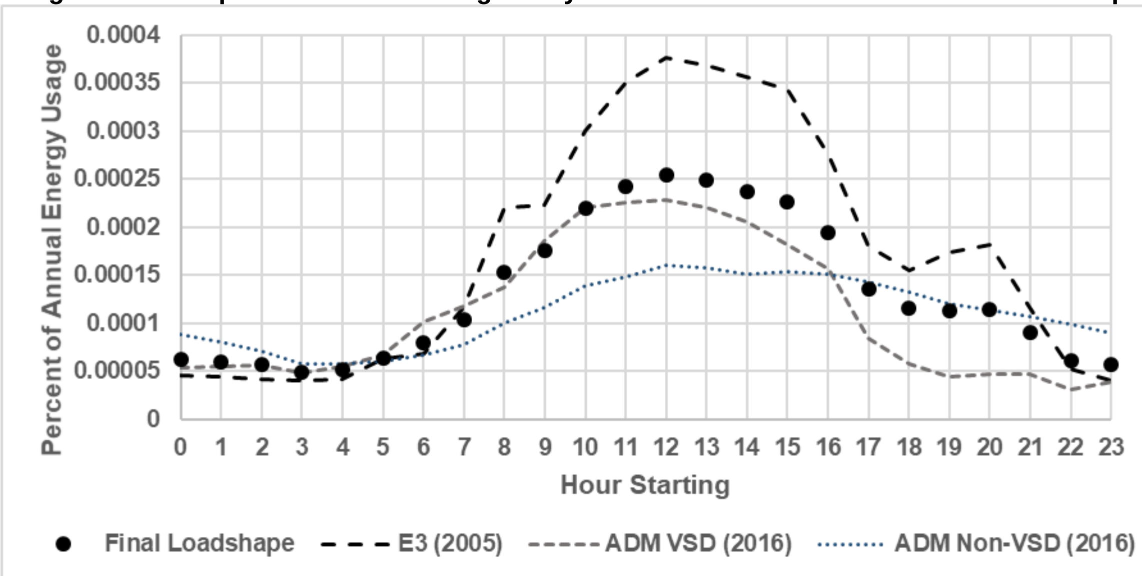
Figure 63: Comparison of the Average Daily Weekday Profile in Summer for Pool Pump



A comparison of the average daily load shape in weekdays in summer for the pool pump end-use as predicted by the 2005 E3 Energy Efficiency Calculator and the 2016 ADM study.

Source: ADM Associates, Inc.

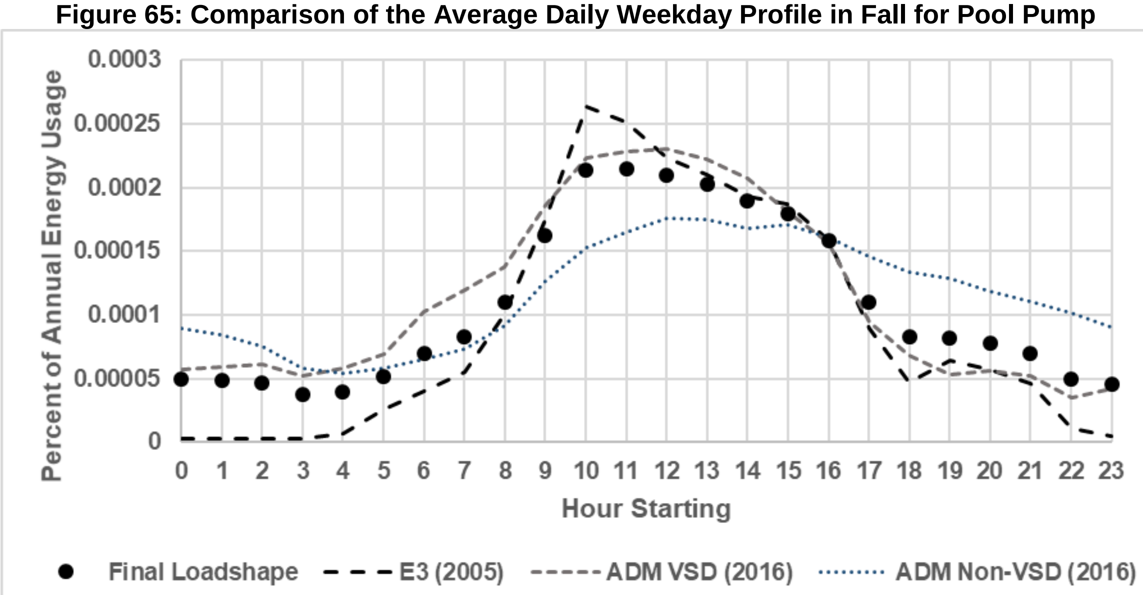
Figure 64: Comparison of the Average Daily Weekend Profile in Summer for Pool Pump



A comparison of the average daily load shape in weekends in summer for the pool pump end-use as predicted by the 2005 E3 Energy Efficiency Calculator and the 2016 ADM study.

Source: ADM Associates, Inc.

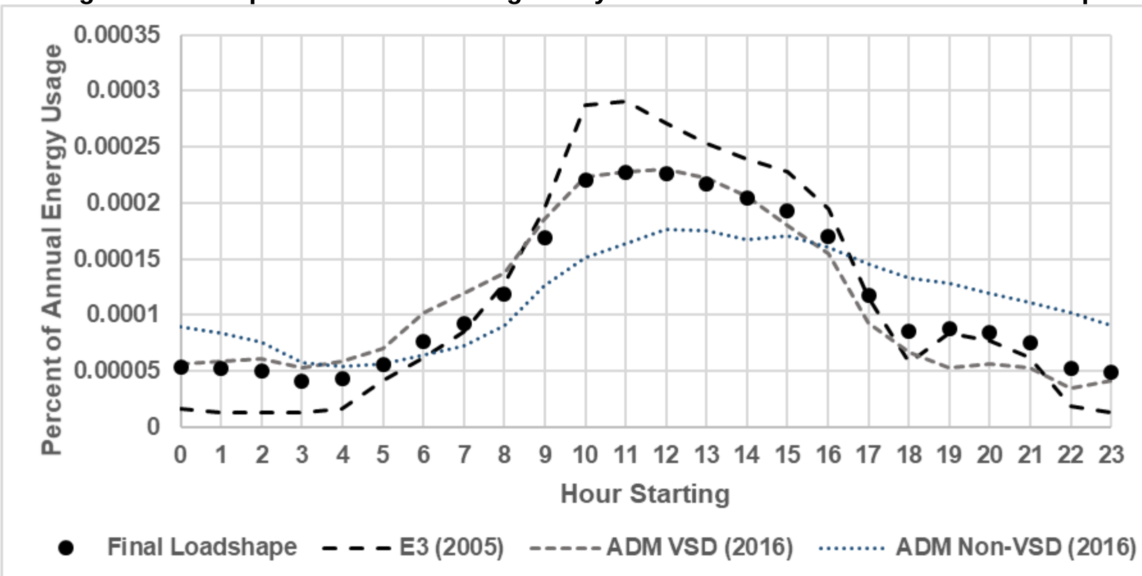
Figure 65: Comparison of the Average Daily Weekday Profile in Fall for Pool Pump



A comparison of the average daily load shape in weekdays in fall for the pool pump end-use as predicted by the 2005 E3 Energy Efficiency Calculator and the 2016 ADM study.

Source: ADM Associates, Inc.

Figure 66: Comparison of the Average Daily Weekend Profile in Fall for Pool Pump



A comparison of the average daily load shape in weekends in fall for the pool pump end-use as predicted by the 2005 E3 Energy Efficiency Calculator and the 2016 ADM study.

Source: ADM Associates, Inc.

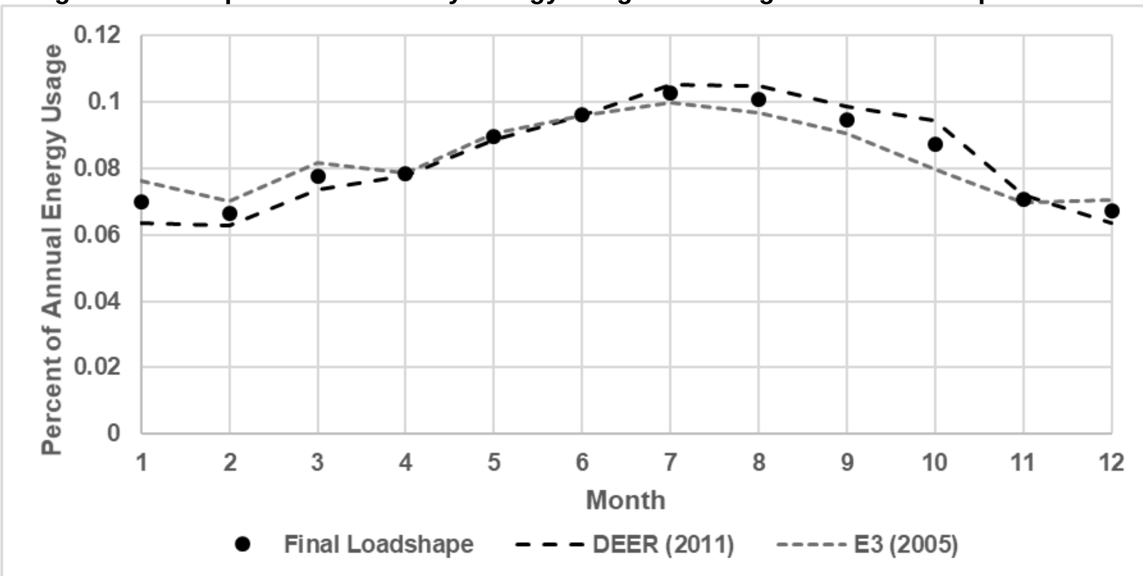
Refrigerator

ADM reviewed two sources for the Refrigerator end-use: the 2011 DEER and the EPRI Load Shape Library V 4.0 (2016).

Figure 67 through

Figure 75 present the monthly energy usage and seasonal weekday/weekend daily profiles for both sources and the aggregated load shape. In general, there was good correspondence, r=0.82, between both sources, therefore, ADM averaged all profiles together to create the final load shape.

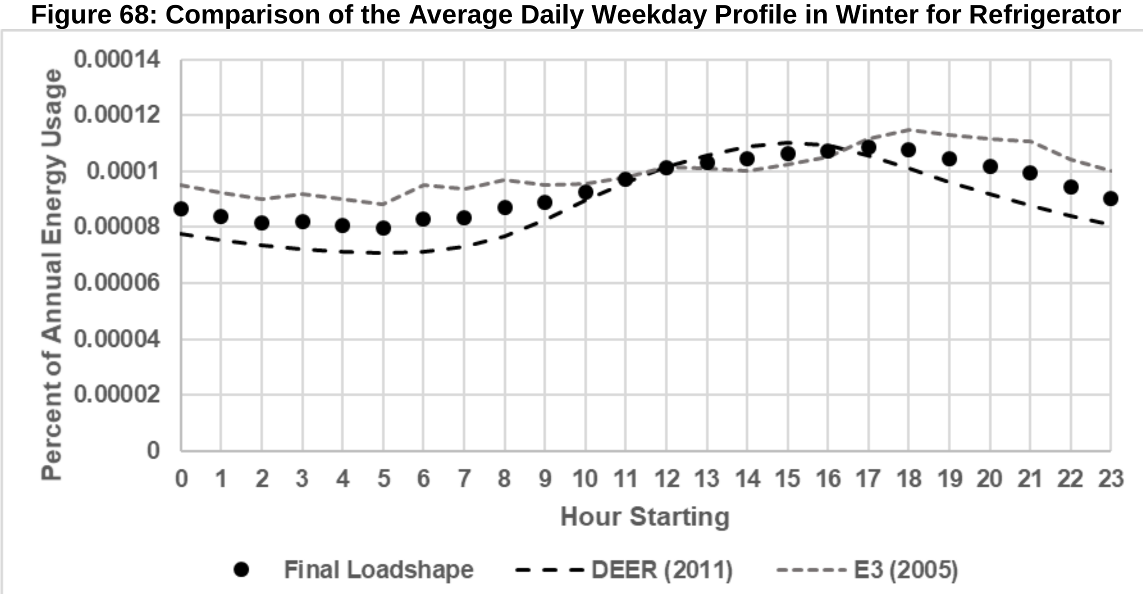
Figure 67: Comparison of Monthly Energy Usage for Refrigerator Load Shape Sources



A comparison of the monthly energy usage for the refrigerator end-use as predicted by the DEER (Itron, Inc. 2011) and E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

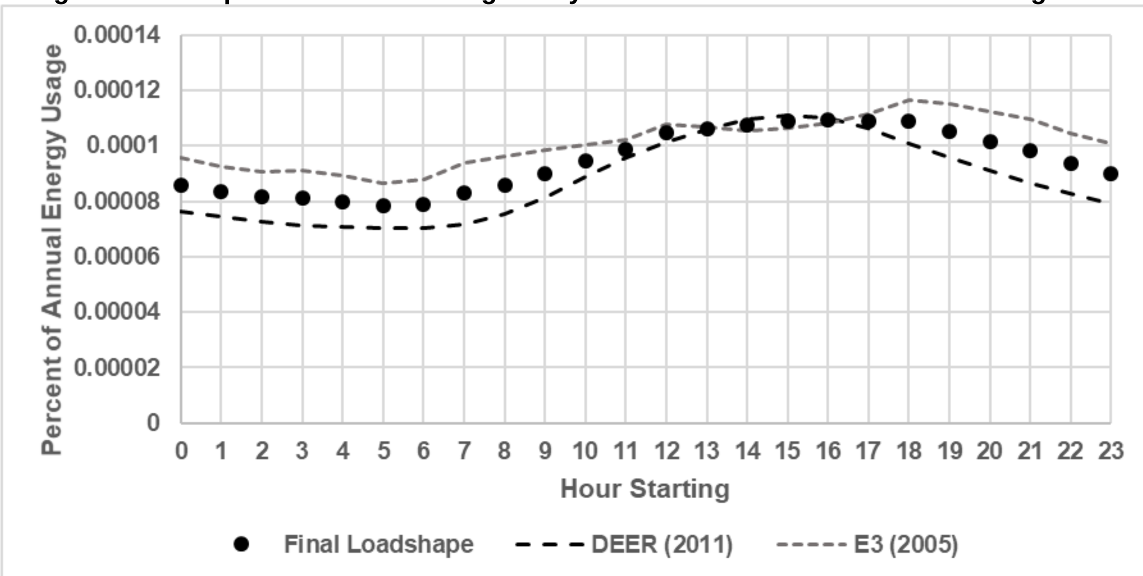
Figure 68: Comparison of the Average Daily Weekday Profile in Winter for Refrigerator



A comparison of the average daily load shape in weekdays in winter for the refrigerator end-use as predicted by the DEER (Itron, Inc. 2011) and E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

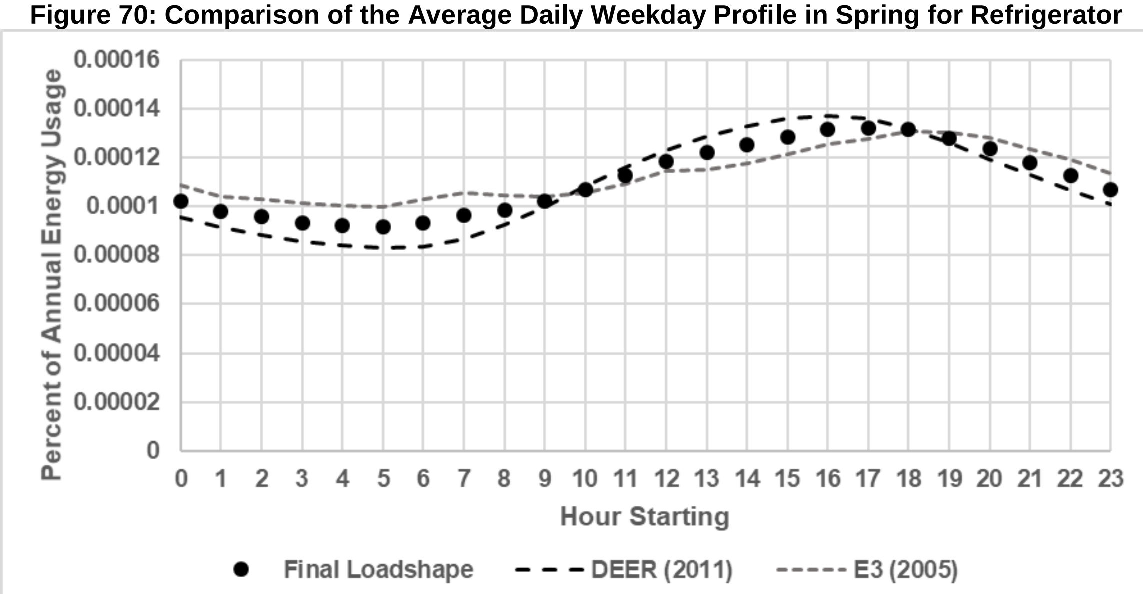
Figure 69: Comparison of the Average Daily Weekend Profile in Winter for Refrigerator



A comparison of the average daily load shape in weekends in winter for the refrigerator end-use as predicted by the DEER (Itron, Inc. 2011) and E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

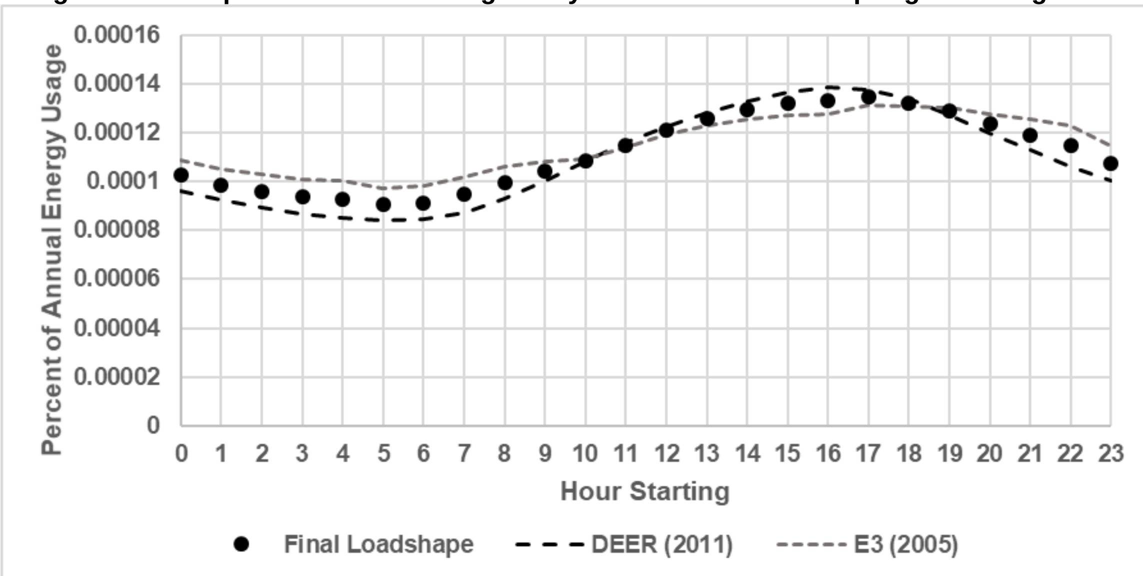
Figure 70: Comparison of the Average Daily Weekday Profile in Spring for Refrigerator



A comparison of the average daily load shape in weekdays in spring for the refrigerator end-use as predicted by the DEER (Itron, Inc. 2011) and E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

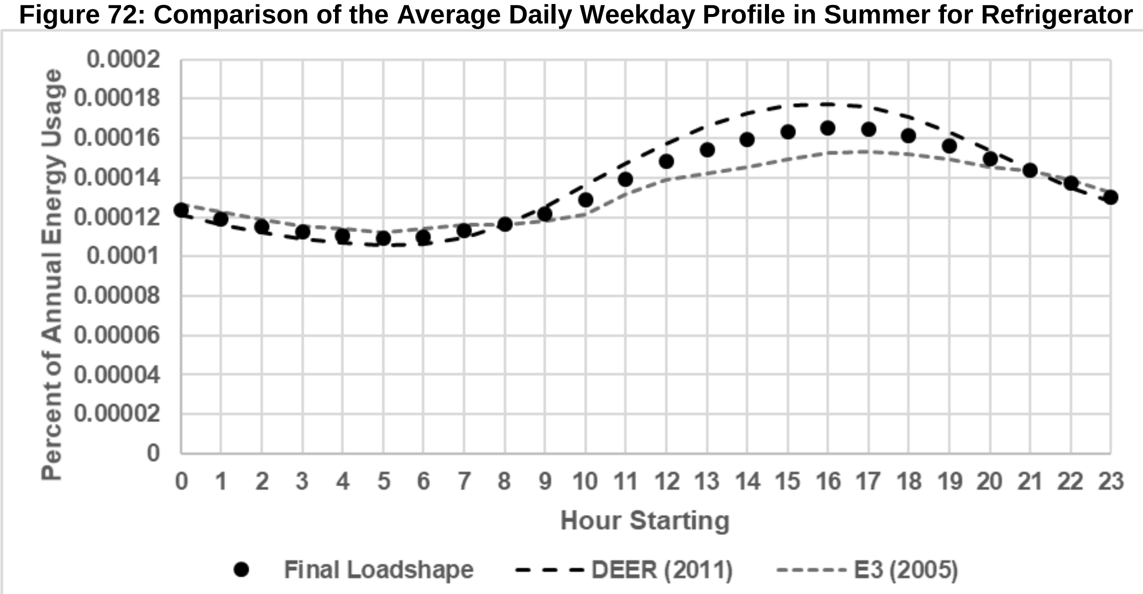
Figure 71: Comparison of the Average Daily Weekend Profile in Spring for Refrigerator



A comparison of the average daily load shape in weekends in spring for the refrigerator end-use as predicted by the DEER (Itron, Inc. 2011) and E3 Energy Efficiency Calculator (2005).

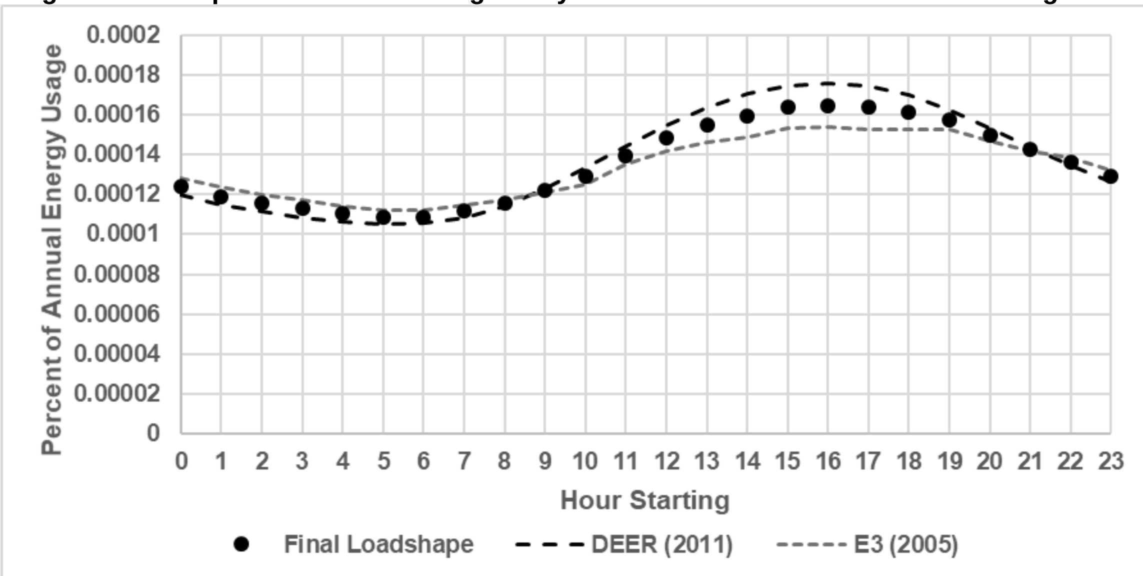
Source: ADM Associates, Inc.

Figure 72: Comparison of the Average Daily Weekday Profile in Summer for Refrigerator



A comparison of the average daily load shape in weekdays in summer for the refrigerator end-use as predicted by the DEER (Itron, Inc. 2011) and E3 Energy Efficiency Calculator (2005). Source: ADM Associates, Inc.

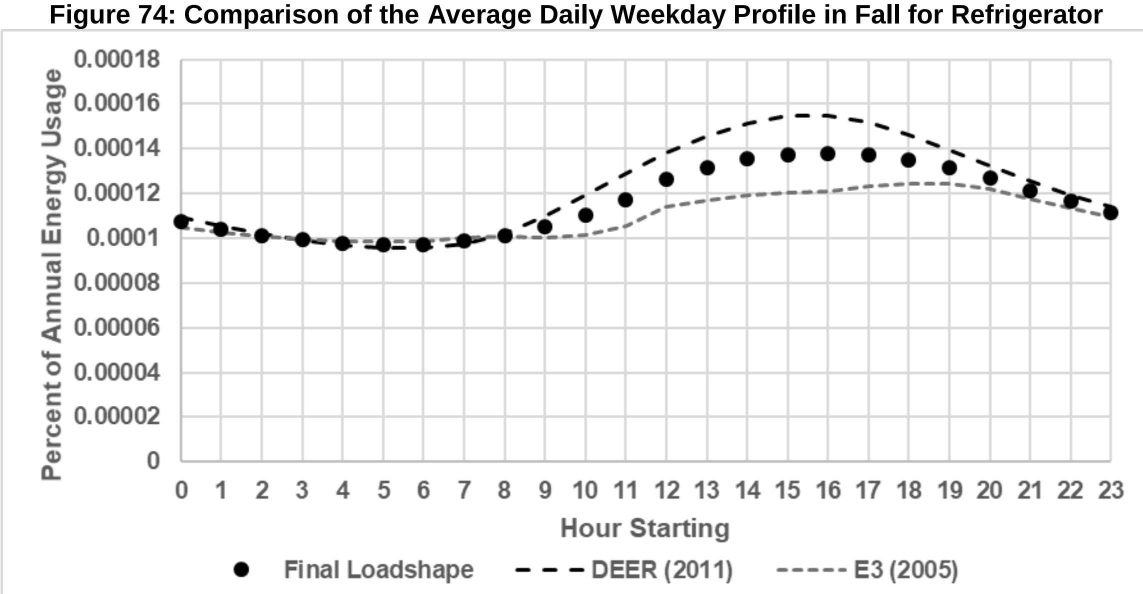
Figure 73: Comparison of the Average Daily Weekend Profile in Summer for Refrigerator



A comparison of the average daily load shape in weekends in summer for the refrigerator end-use as predicted by the DEER (Itron, Inc. 2011) and E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

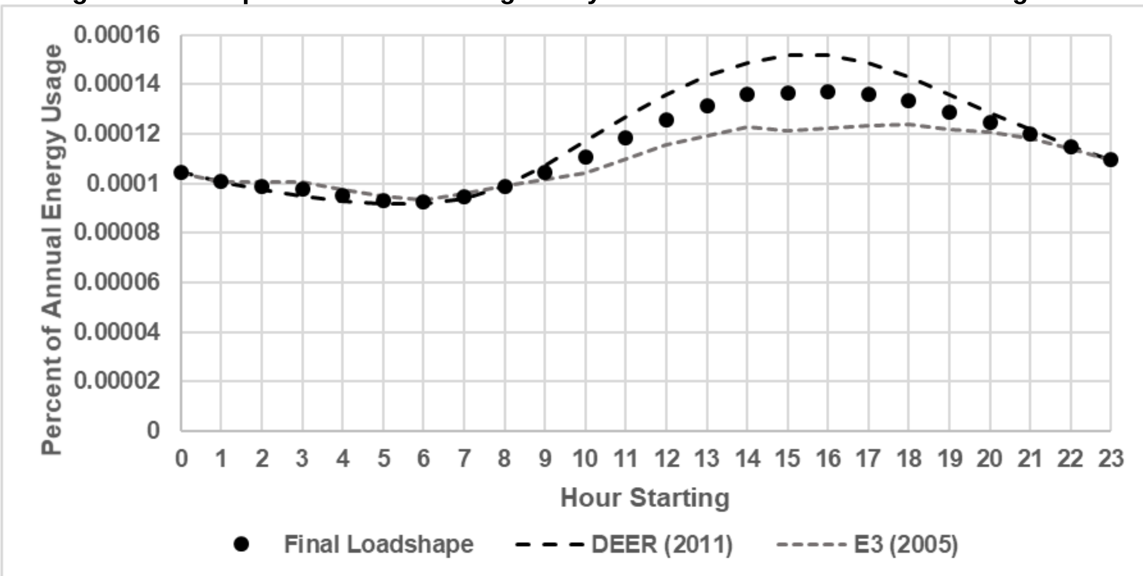
Figure 74: Comparison of the Average Daily Weekday Profile in Fall for Refrigerator



A comparison of the average daily load shape in weekdays in fall for the refrigerator end-use as predicted by the DEER (Itron, Inc. 2011) and E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

Figure 75: Comparison of the Average Daily Weekend Profile in Fall for Refrigerator



A comparison of the average daily load shape in weekends in fall for the refrigerator end-use as predicted by the DEER (Itron, Inc. 2011) and E3 Energy Efficiency Calculator (2005).

Source: ADM Associates, Inc.

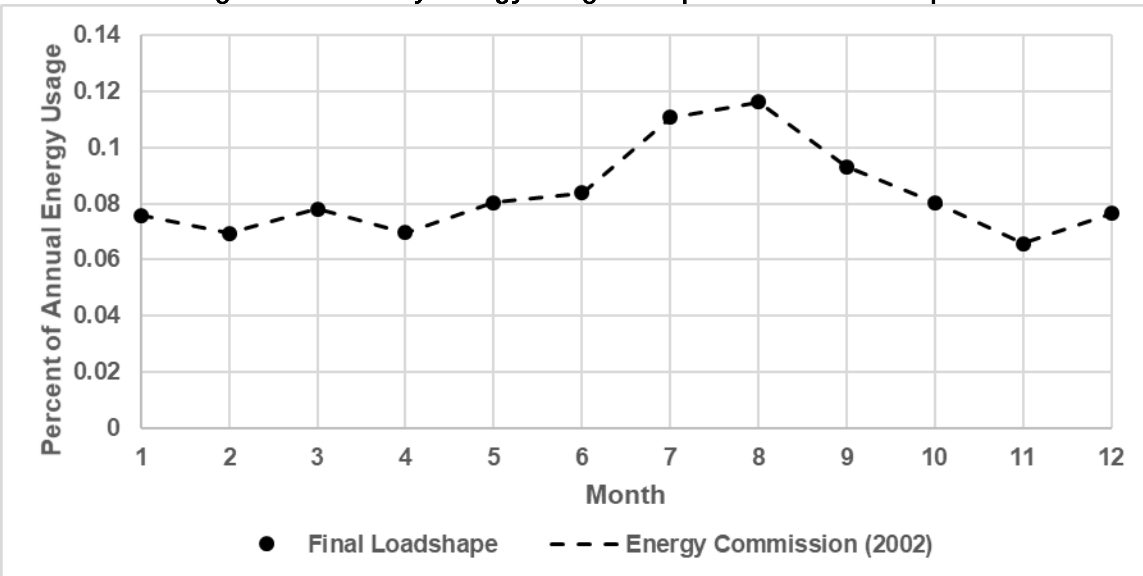
Spa Heater

Spa heaters are an uncommon end-use, with the percent of homes having this end-use ranging from less than 0.1% to 9% depending on the utility company (Palmgren et al. 2010). The number of resources with an isolated spa heater load shape was limited. Therefore, ADM passed through the Energy Commission's existing load shape as updated in 2002.

Figure 76 through

Figure 84 present the monthly energy usage and seasonal weekday/weekend daily profiles for this load shape.

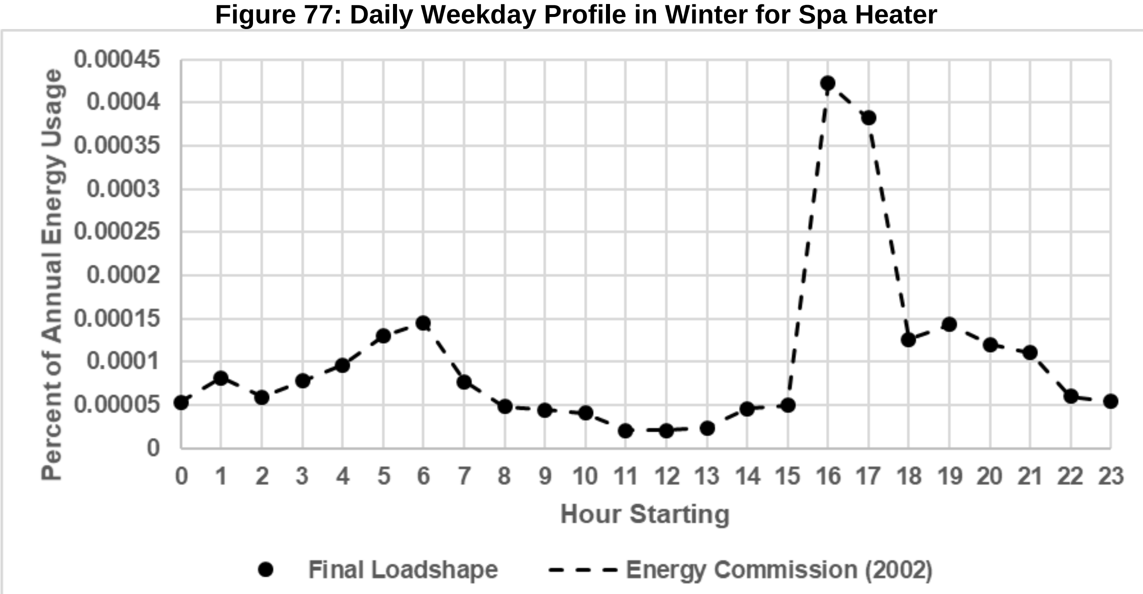
Figure 76: Monthly Energy Usage for Spa Heater Load Shape



A comparison of the monthly energy usage for spa heater as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

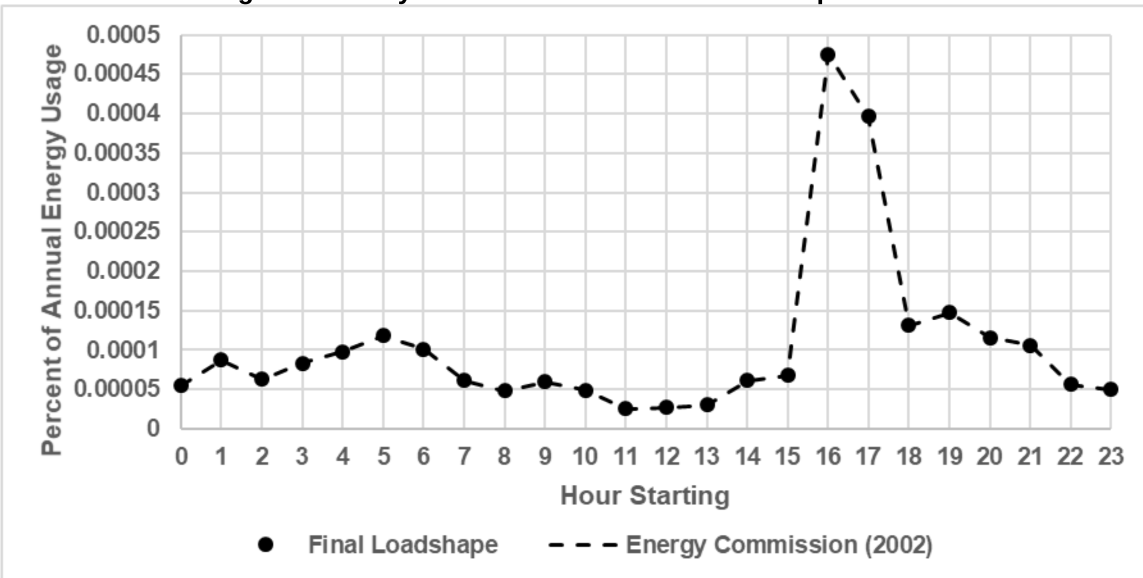
Figure 77: Daily Weekday Profile in Winter for Spa Heater



A comparison of the average daily load shape in weekdays in winter for the spa heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

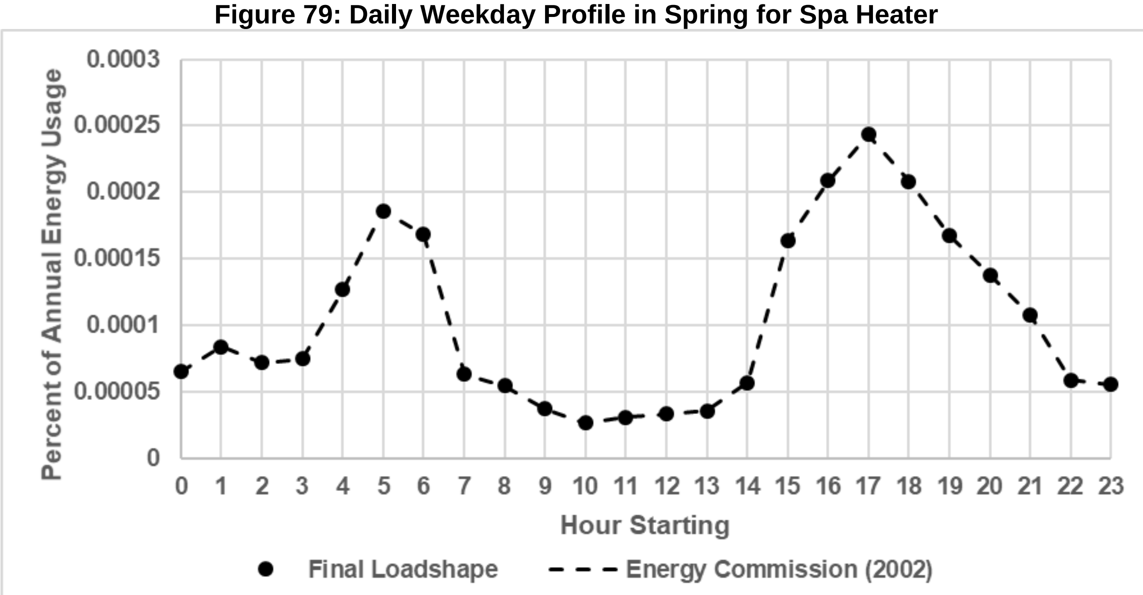
Figure 78: Daily Weekend Profile in Winter for Spa Heater



A comparison of the average daily load shape in weekends in winter for the spa heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

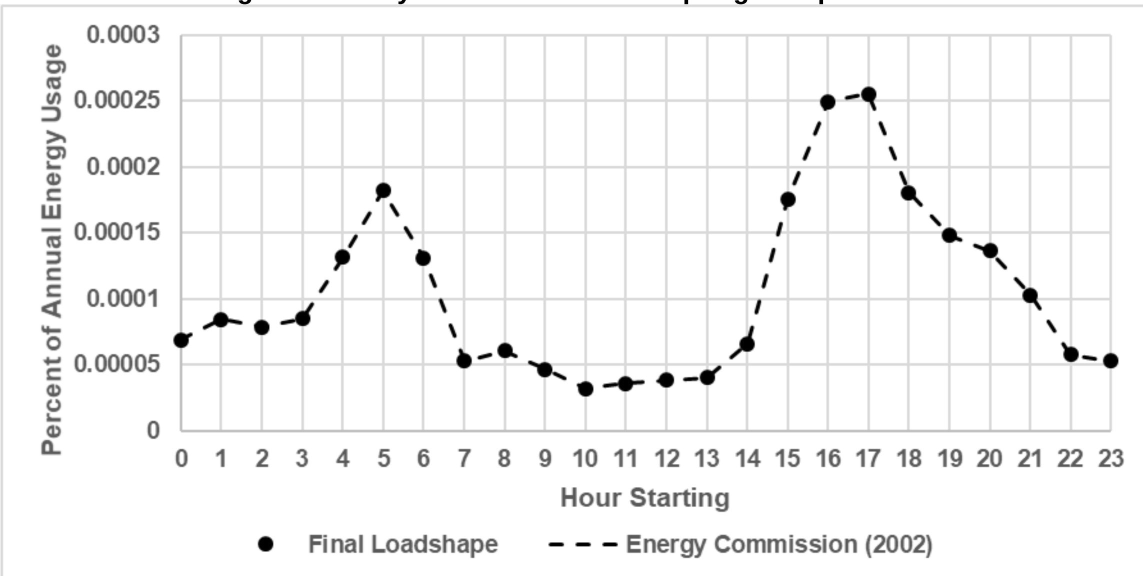
Figure 79: Daily Weekday Profile in Spring for Spa Heater



A comparison of the average daily load shape in weekdays in spring for the spa heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

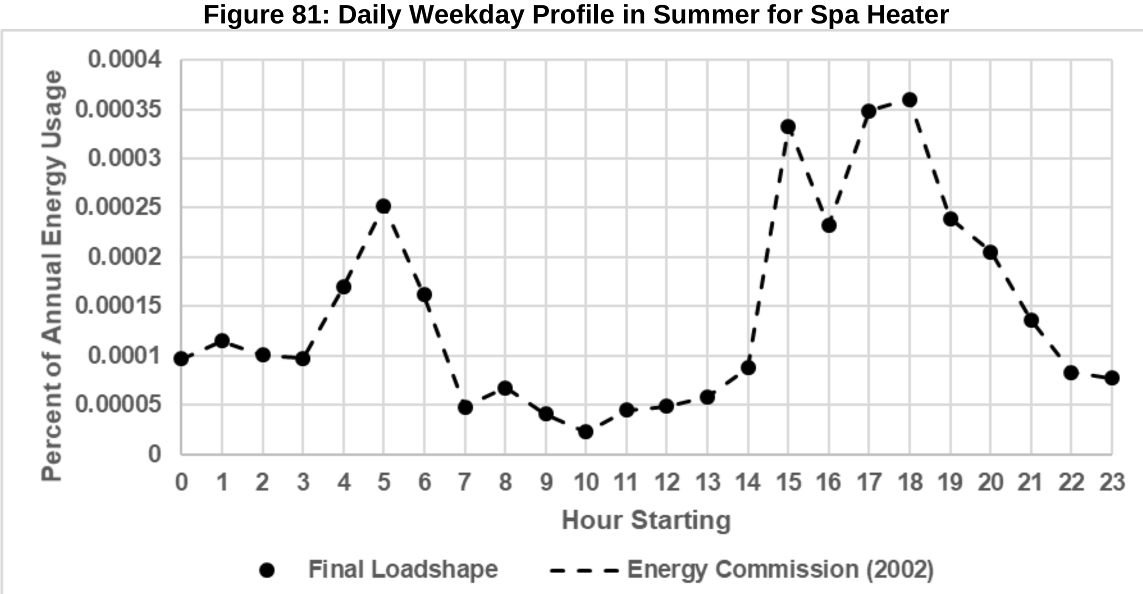
Figure 80: Daily Weekend Profile in Spring for Spa Heater



A comparison of the average daily load shape in weekends in spring for the spa heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

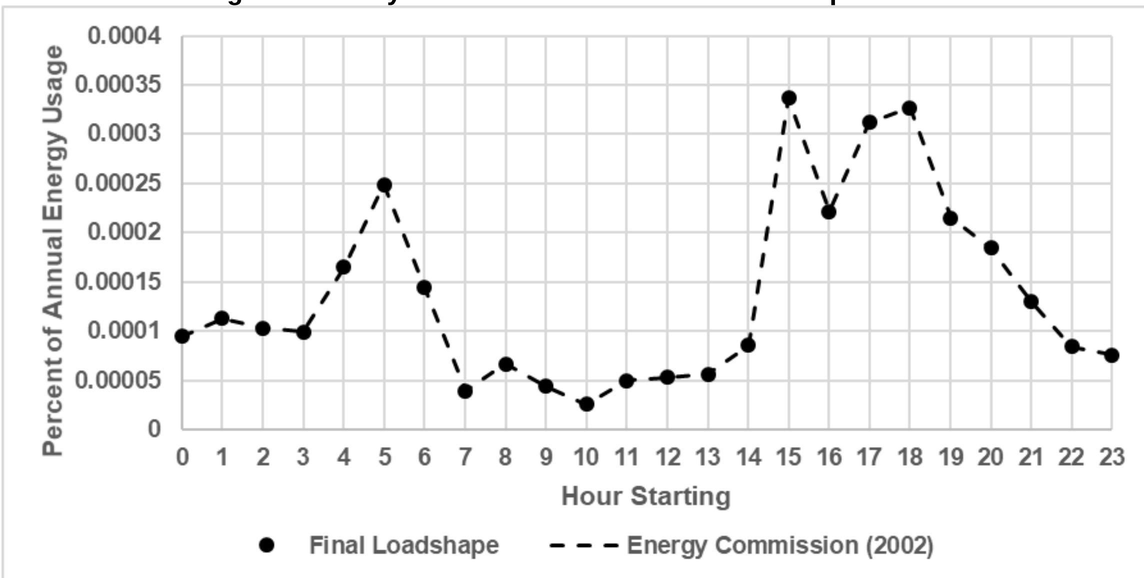
Figure 81: Daily Weekday Profile in Summer for Spa Heater



A comparison of the average daily load shape in weekdays in summer for the spa heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

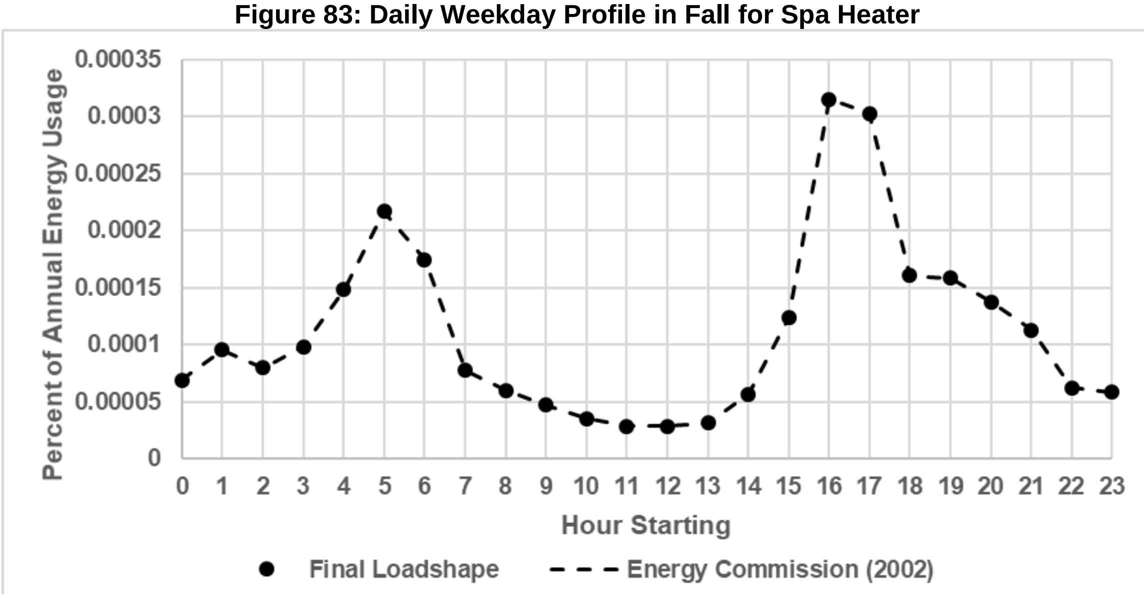
Figure 82: Daily Weekend Profile in Summer for Spa Heater



A comparison of the average daily load shape in weekends in summer for the spa heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

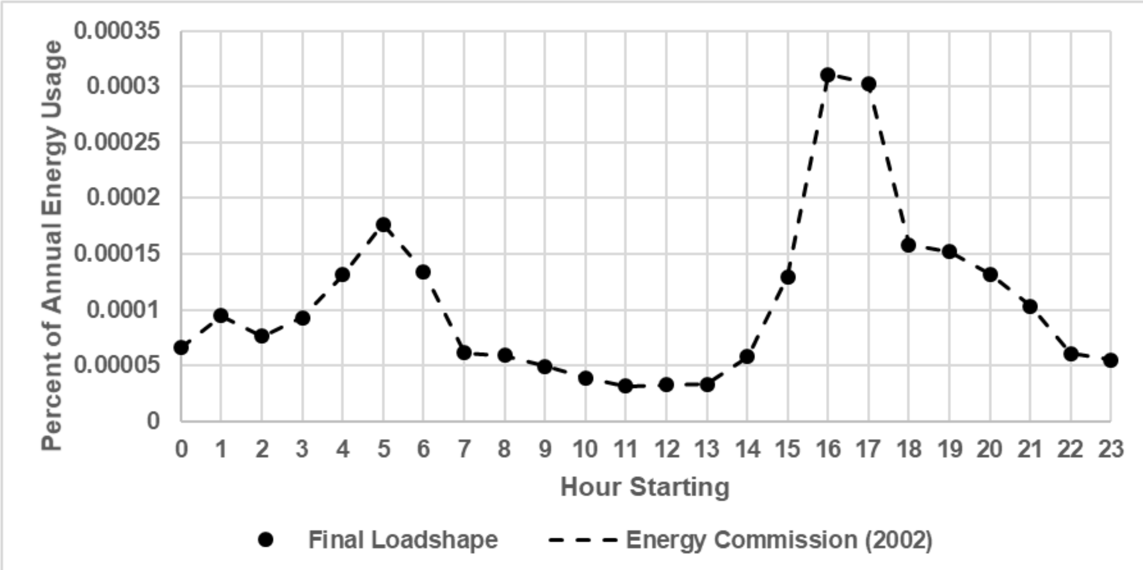
Figure 83: Daily Weekday Profile in Fall for Spa Heater



A comparison of the average daily load shape in weekdays in fall for the spa heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

Figure 84: Daily Weekend Profile in Fall for Spa Heater



A comparison of the average daily load shape in weekends in fall for the spa heater end-use as predicted by the 2002 Energy Commission load shape.

Source: ADM Associates, Inc.

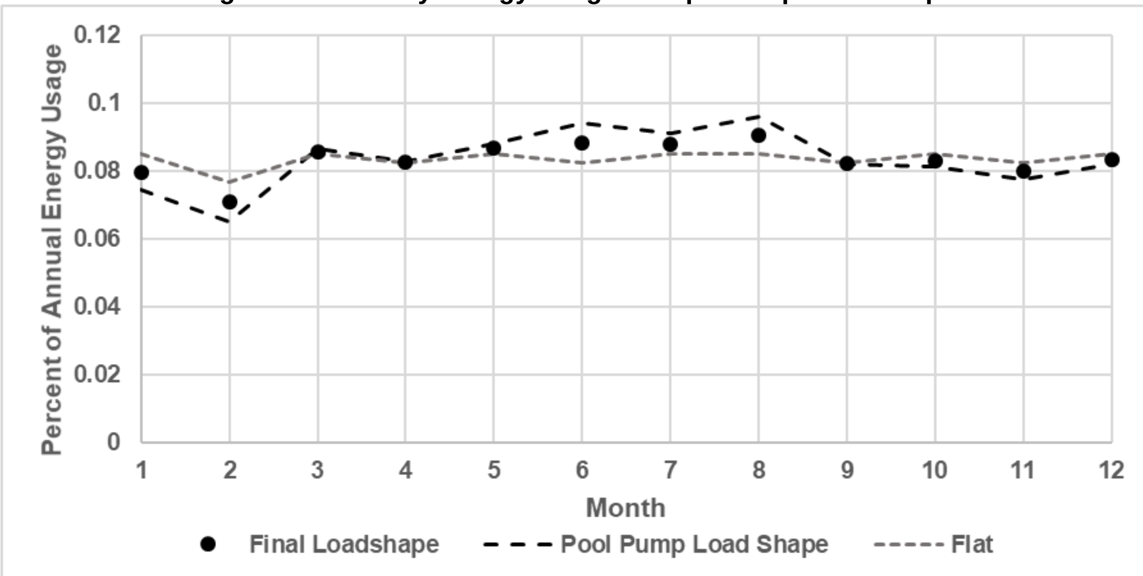
Spa Pump

Spa pumps are not a well-studied end-use. None of the sources reviewed as part of ADM's literature review featured an isolate spa pump load shape; instead choosing to aggregate across spa and pool pumps. Part of this may be due to spa pumps contributing less than 0.1% of the average annual energy load of a home, thereby making its impact low compared to other end-uses (Palmgren et al. 2010). ADM generally assumed that the load shape for spa pumps should be collinear to the load shape for pool pumps, with a more distributed load shape as energy demand of a spa pump is lower than that of a pool pump. To accomplish this, ADM used the consolidated pool pump load shape and averaged it with a static flat load shape.

Figure 85 through

Figure 93 present the monthly energy usage and seasonal weekday/weekend daily profiles for this load shape.

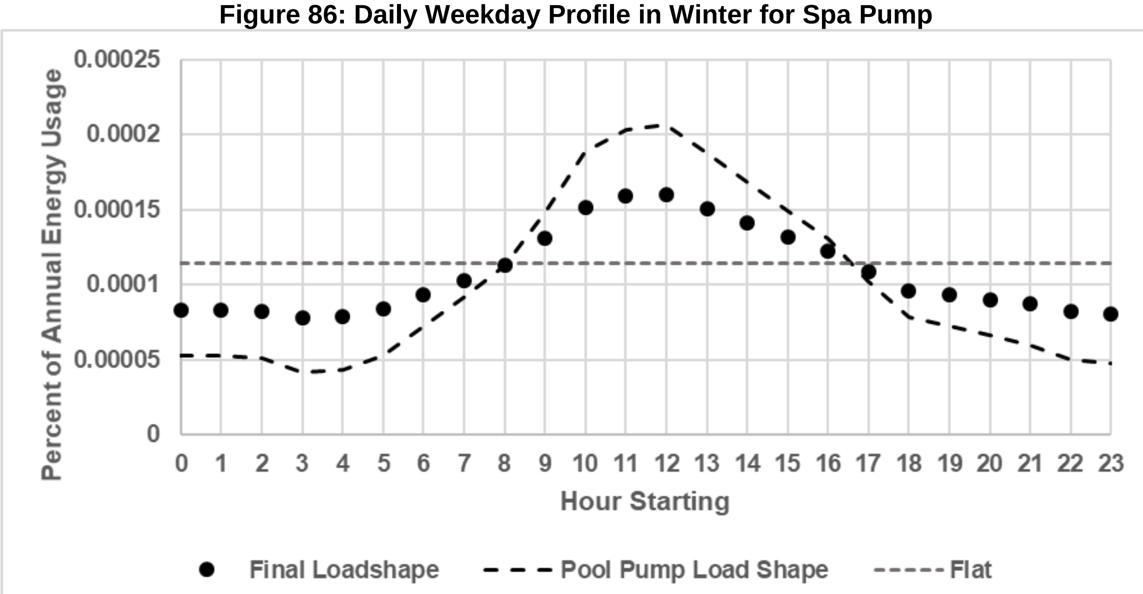
Figure 85: Monthly Energy Usage for Spa Pump Load Shape



A comparison of the monthly energy usage for spa pump as compared to the pool pump load shape and a static flat load shape.

Source: ADM Associates, Inc.

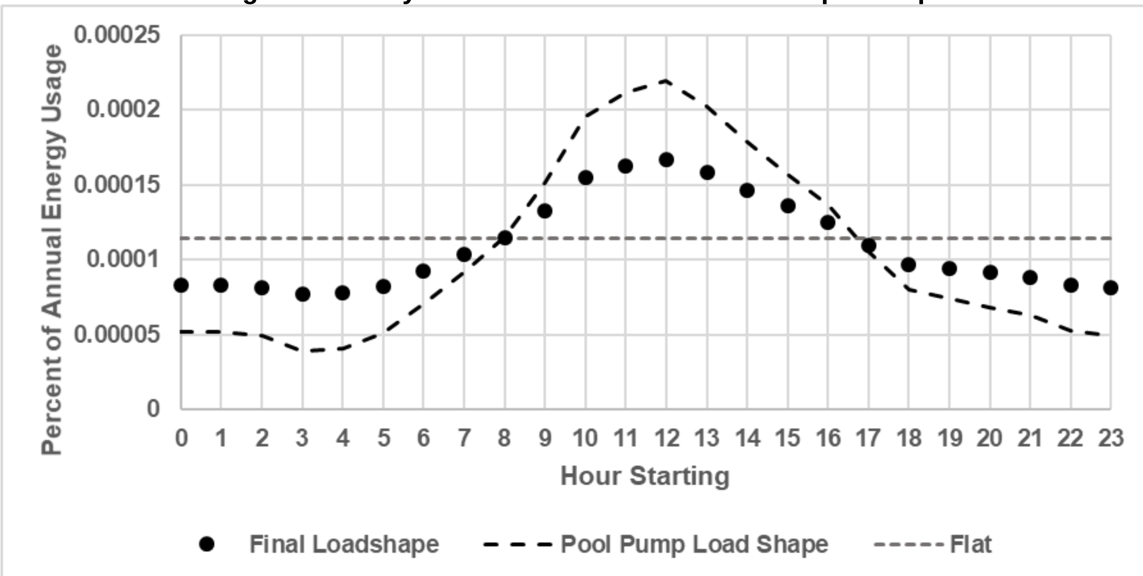
Figure 86: Daily Weekday Profile in Winter for Spa Pump



A comparison of the average daily load shape in weekdays in winter for spa pump as compared to the pool pump load shape and a static flat load shape.

Source: ADM Associates, Inc.

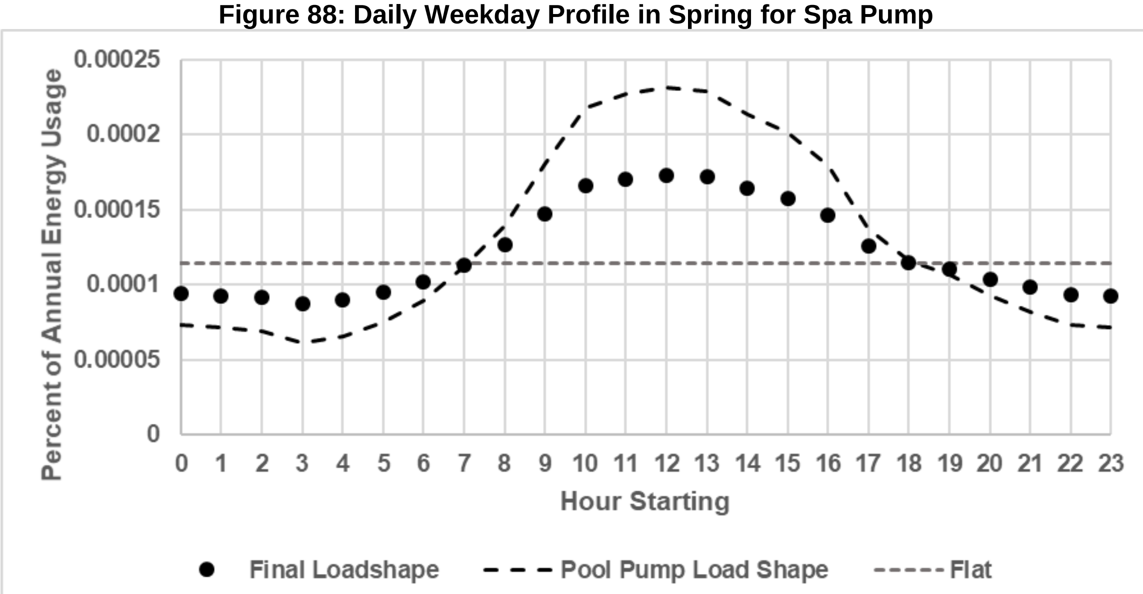
Figure 87: Daily Weekend Profile in Winter for Spa Pump



A comparison of the average daily load shape in weekends in winter for spa pump as compared to the pool pump load shape and a static flat load shape.

Source: ADM Associates, Inc.

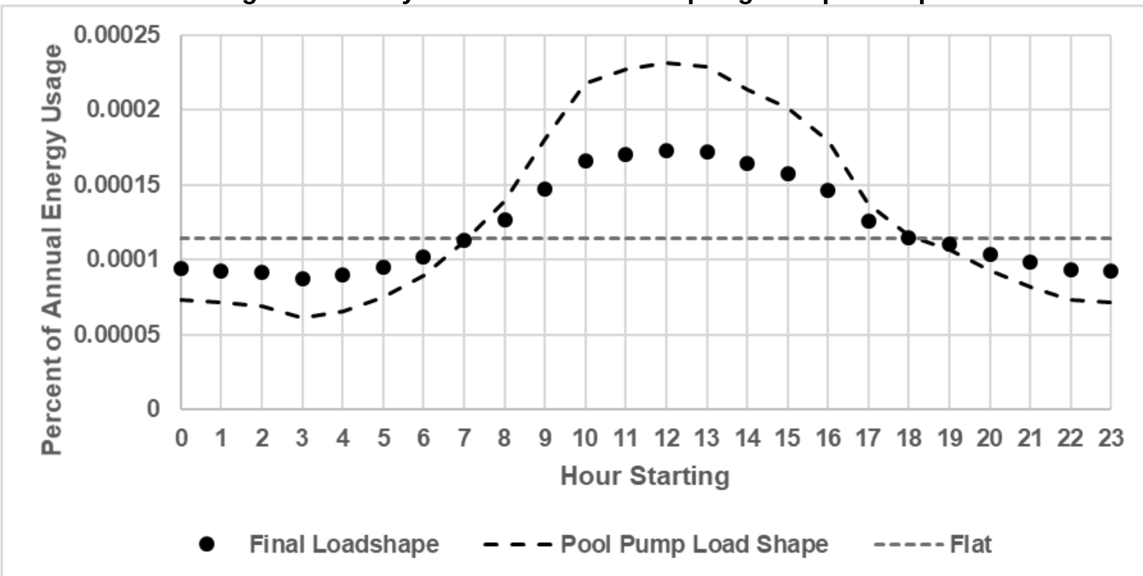
Figure 88: Daily Weekday Profile in Spring for Spa Pump



A comparison of the average daily load shape in weekdays in spring for spa pump as compared to the pool pump load shape and a static flat load shape.

Source: ADM Associates, Inc.

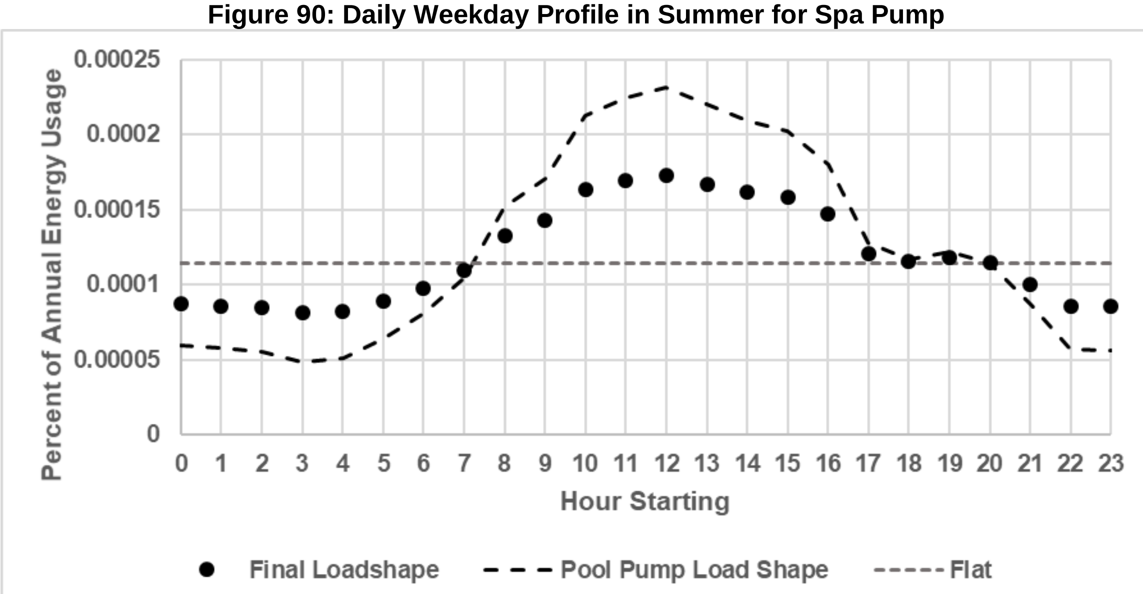
Figure 89: Daily Weekend Profile in Spring for Spa Pump



A comparison of the average daily load shape in weekends in spring for spa pump as compared to the pool pump load shape and a static flat load shape.

Source: ADM Associates, Inc.

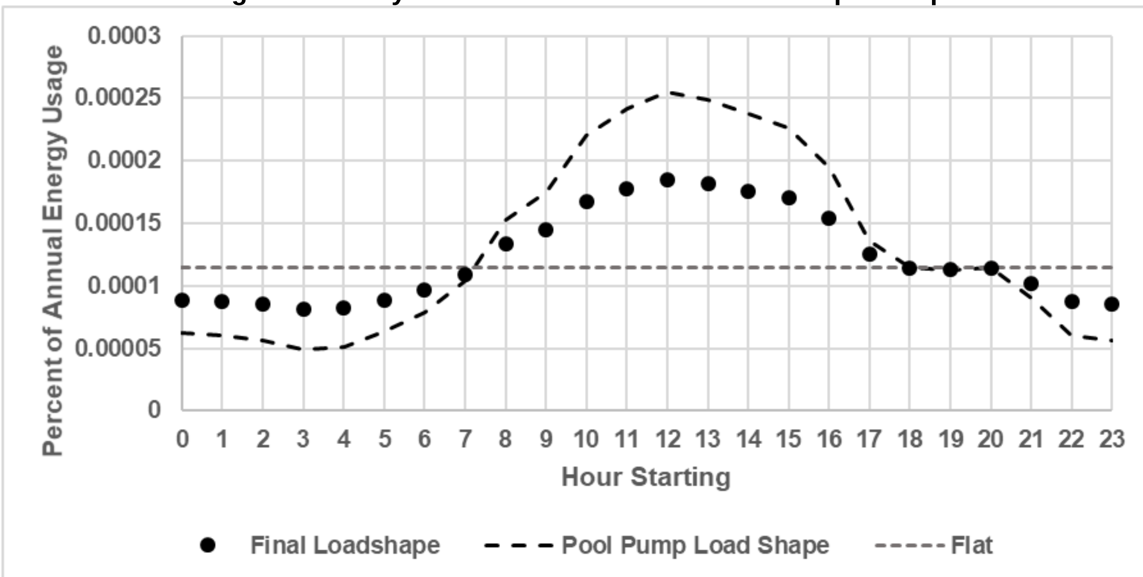
Figure 90: Daily Weekday Profile in Summer for Spa Pump



A comparison of the average daily load shape in weekdays in summer for spa pump as compared to the pool pump load shape and a static flat load shape.

Source: ADM Associates, Inc.

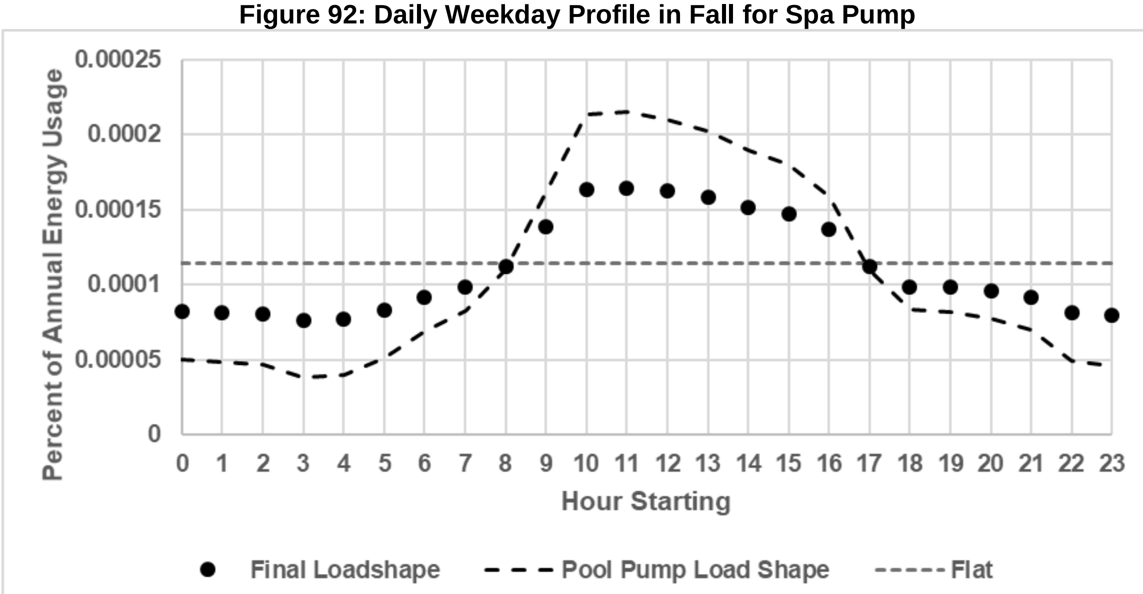
Figure 91: Daily Weekend Profile in Summer for Spa Pump



A comparison of the average daily load shape in weekends in summer for spa pump as compared to the pool pump load shape and a static flat load shape.

Source: ADM Associates, Inc.

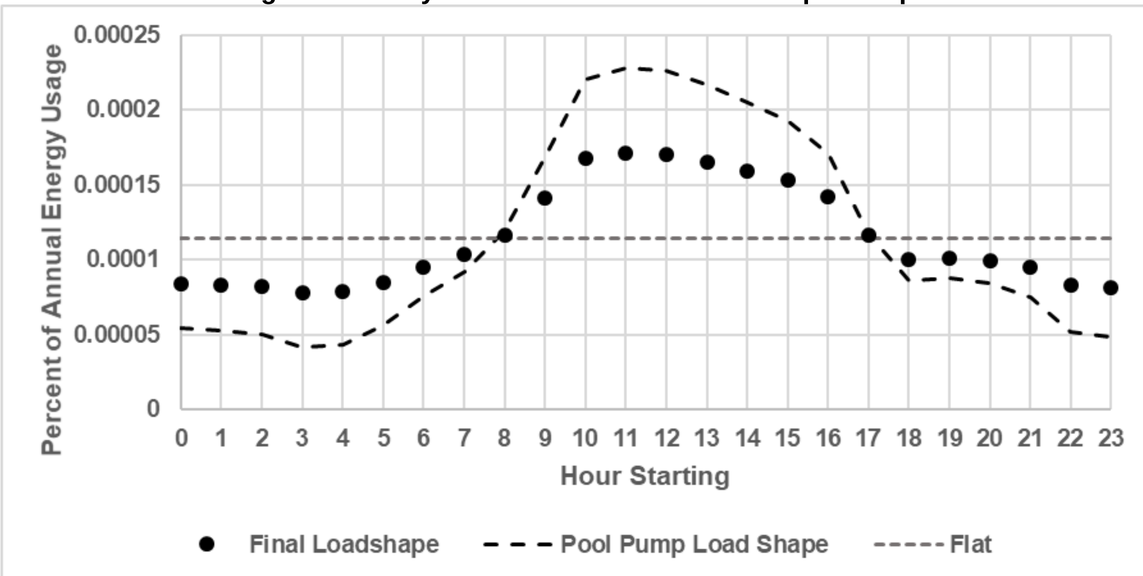
Figure 92: Daily Weekday Profile in Fall for Spa Pump



A comparison of the average daily load shape in weekdays in fall for spa pump as compared to the pool pump load shape and a static flat load shape.

Source: ADM Associates, Inc.

Figure 93: Daily Weekend Profile in Fall for Spa Pump



A comparison of the average daily load shape in weekends in fall for spa pump as compared to the pool pump load shape and a static flat load shape.

Source: ADM Associates, Inc.

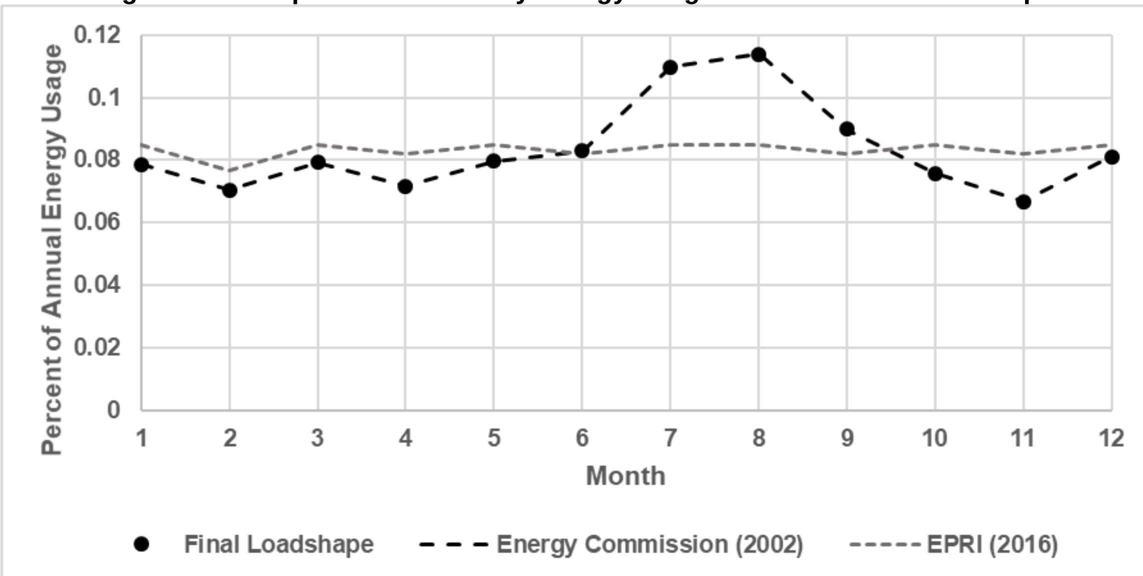
Television

In addition to the Energy Commission's 2002 load shape, ADM was able to locate one additional data source for a television load shape. This secondary source came from the 2016 EPRI Load Shape Library 4.0. Unlike the Energy Commission load shape, however, the EPRI shape also includes consumer electronics such as telecommunications, computers, etc. In general, load shapes for television or consumer electronics should follow a similar pattern to a lighting load shape, with an off-hours peak in the mid-evening and a low-point in the early morning. Because the EPRI load shape showed anomalous patterning, ADM reverted to using the Energy Commission's 2002 load shape for television.

Figure 94 through

Figure 102 present this comparison.

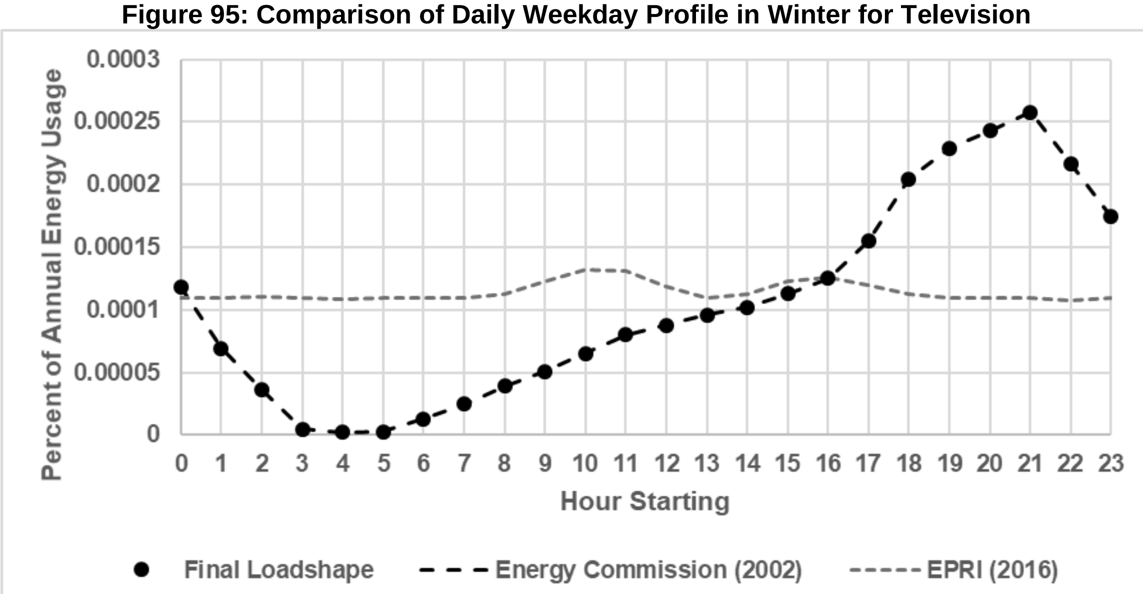
Figure 94: Comparison of Monthly Energy Usage for Television Load Shape



A comparison of the monthly energy usage for television between the 2002 Energy Commission load shape and the 2016 EPRI load shape.

Source: ADM Associates, Inc.

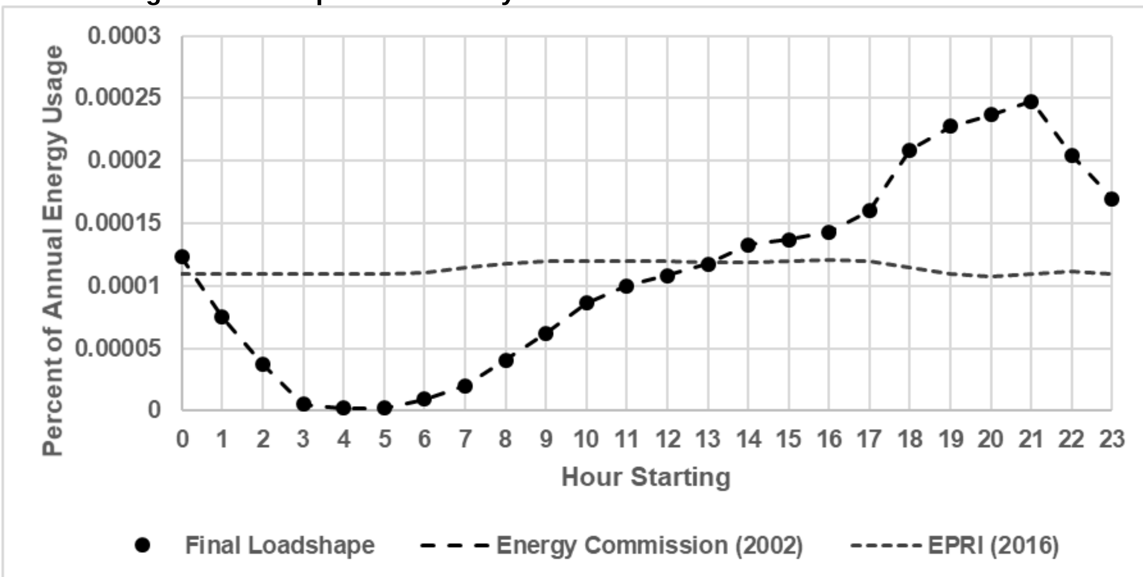
Figure 95: Comparison of Daily Weekday Profile in Winter for Television



A comparison of the average daily load shape in weekdays in winter for television between the 2002 Energy Commission load shape and the 2016 EPRI load shape.

Source: ADM Associates, Inc.

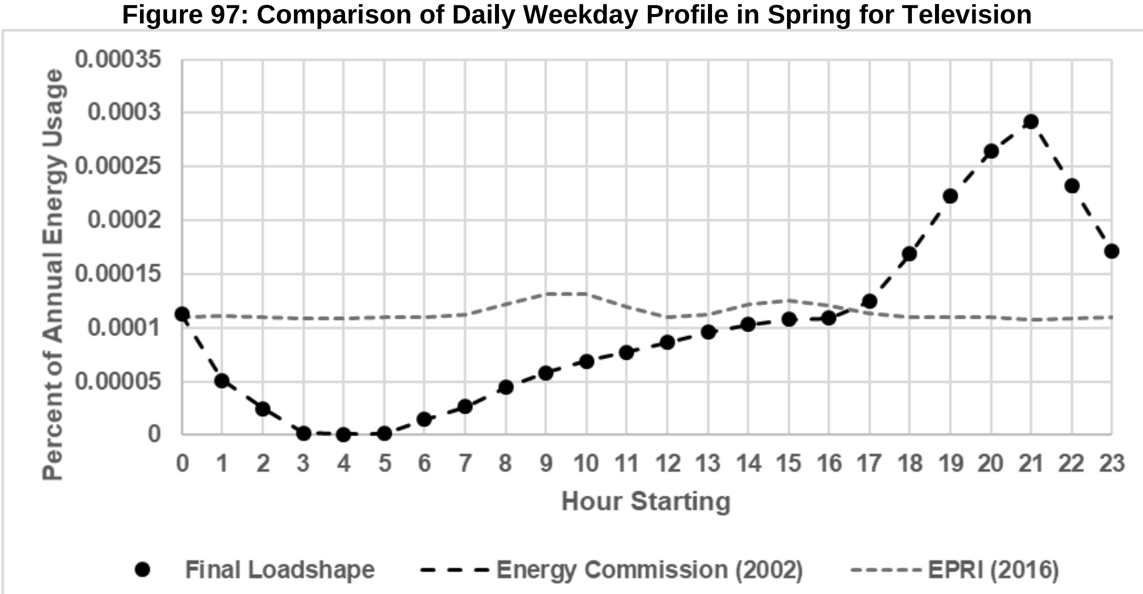
Figure 96: Comparison of Daily Weekend Profile in Winter for Television



A comparison of the average daily load shape in weekends in winter for television between the 2002 Energy Commission load shape and the 2016 EPRI load shape.

Source: ADM Associates, Inc.

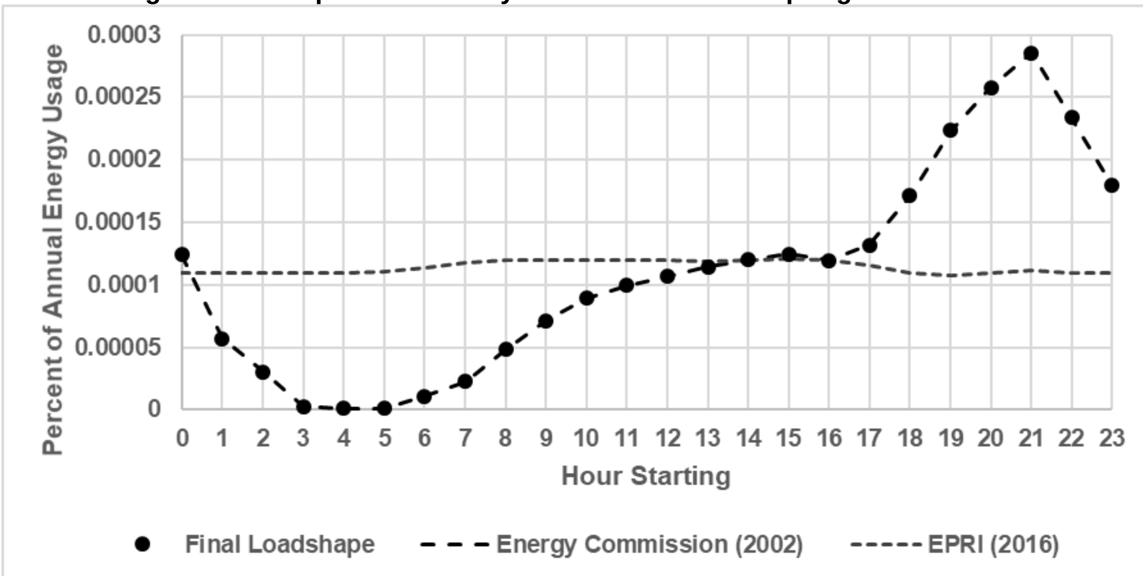
Figure 97: Comparison of Daily Weekday Profile in Spring for Television



A comparison of the average daily load shape in weekdays in spring for television between the 2002 Energy Commission load shape and the 2016 EPRI load shape.

Source: ADM Associates, Inc.

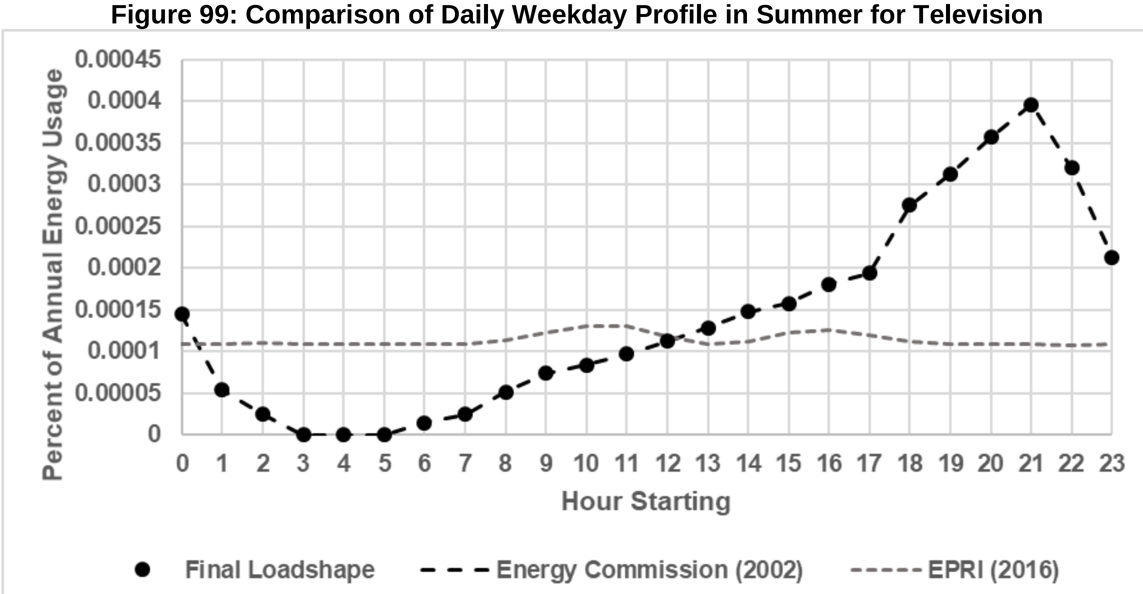
Figure 98: Comparison of Daily Weekend Profile in Spring for Television



A comparison of the average daily load shape in weekends in spring for television between the 2002 Energy Commission load shape and the 2016 EPRI load shape.

Source: ADM Associates, Inc.

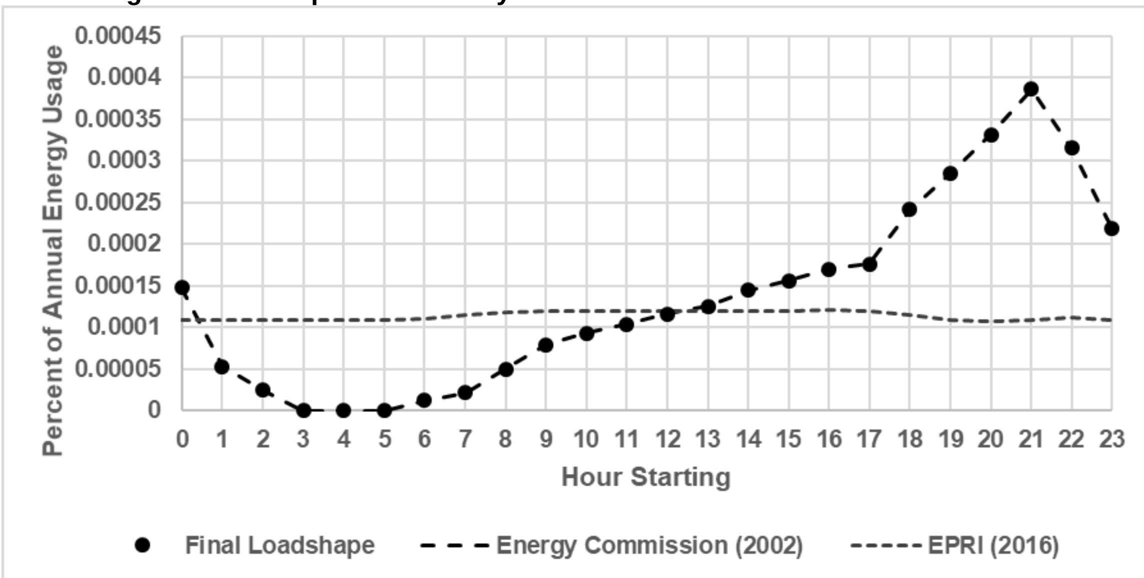
Figure 99: Comparison of Daily Weekday Profile in Summer for Television



A comparison of the average daily load shape in weekdays in summer for television between the 2002 Energy Commission load shape and the 2016 EPRI load shape.

Source: ADM Associates, Inc.

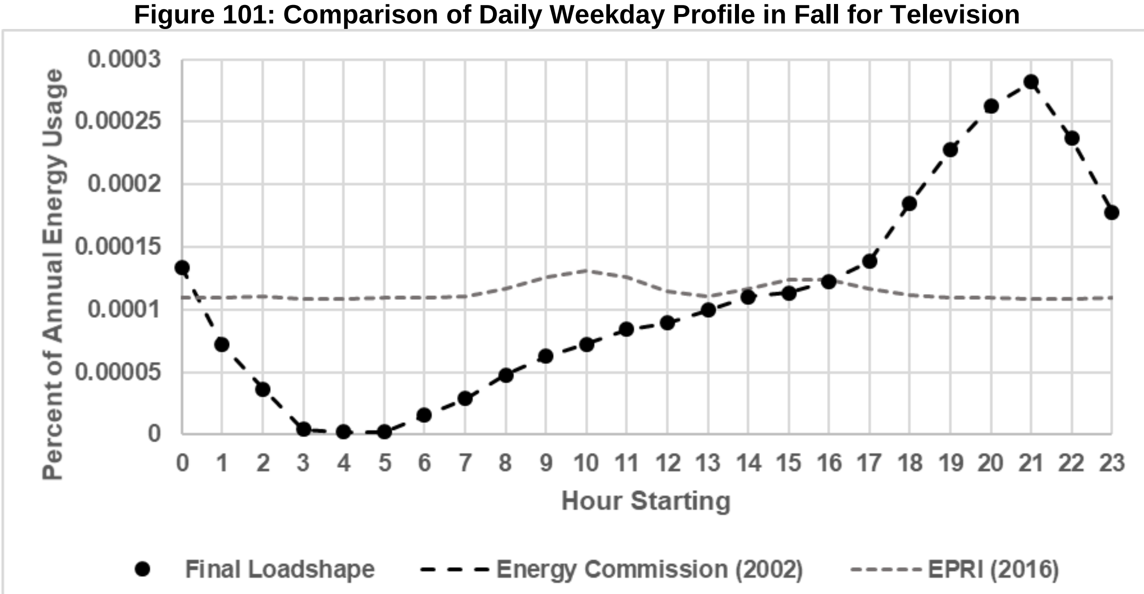
Figure 100: Comparison of Daily Weekend Profile in Summer for Television



A comparison of the average daily load shape in weekends in summer for television between the 2002 Energy Commission load shape and the 2016 EPRI load shape.

Source: ADM Associates, Inc.

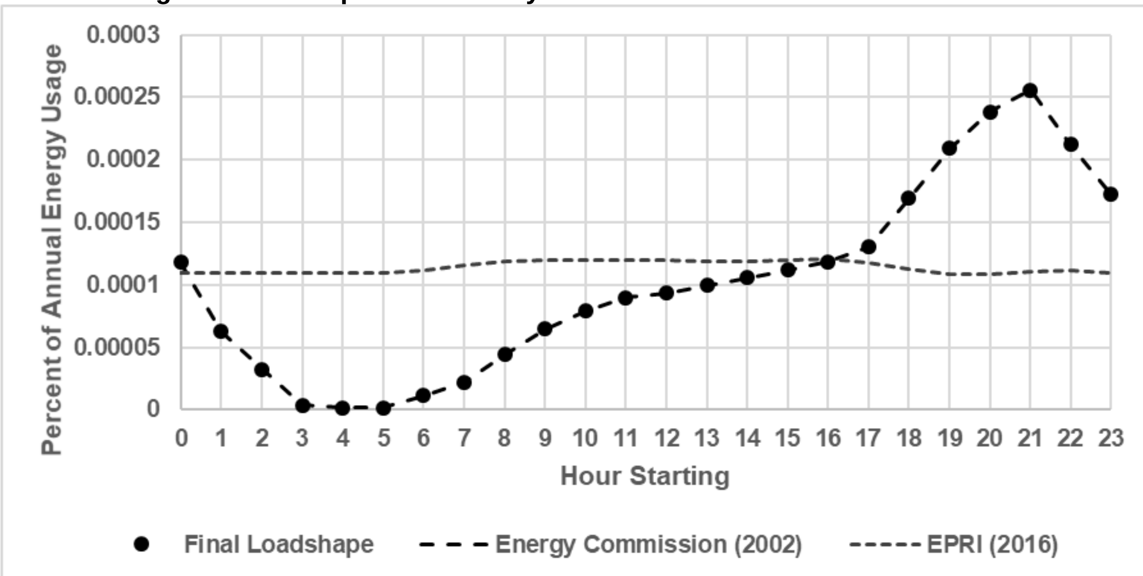
Figure 101: Comparison of Daily Weekday Profile in Fall for Television



A comparison of the average daily load shape in weekdays in fall for television between the 2002 Energy Commission load shape and the 2016 EPRI load shape.

Source: ADM Associates, Inc.

Figure 102: Comparison of Daily Weekend Profile in Fall for Television



A comparison of the average daily load shape in weekends in fall for television between the 2002 Energy Commission load shape and the 2016 EPRI load shape.

Source: ADM Associates, Inc.

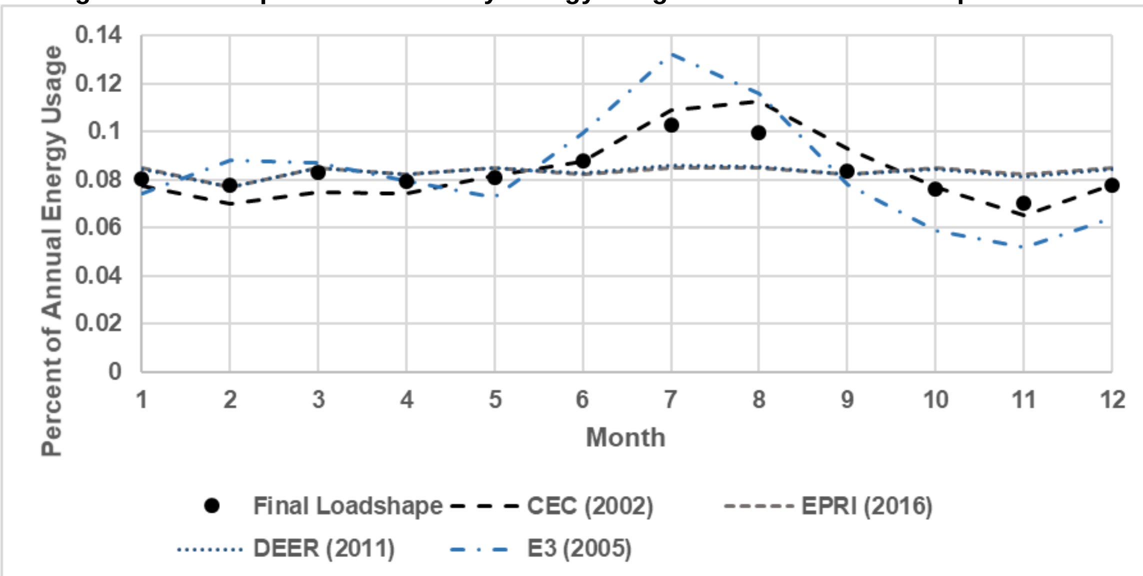
Washer

ADM reviewed four sources for the washer end-use: the existing Energy Commission load shape from 2002, the 2016 EPRI Load Shape Library 4.0, the DEER (Itron, Inc. 2011), and the E3 Energy Efficiency Calculator (2005). Although there was a fair amount of volatility between the four data sources, an argument could not be made as to why one profile may be more valid than the other, therefore, ADM averaged all profiles together to create the final load shape.

Figure 103 through

Figure 111 present a comparison of the different load shapes sourced for this project.

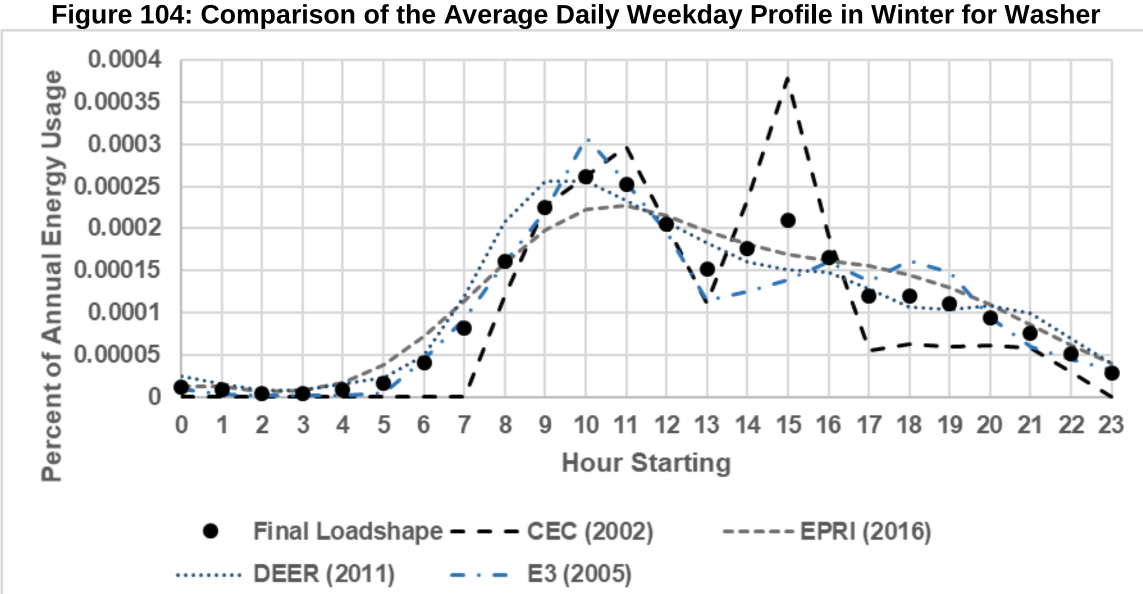
Figure 103: Comparison of Monthly Energy Usage for Washer Load Shape Sources



A comparison of the monthly energy usage for the washer end-use as predicted by the Energy Commission (2002), EPRI (2016), DEER (Itron, Inc. 2011), and E3 (2005).

Source: ADM Associates, Inc.

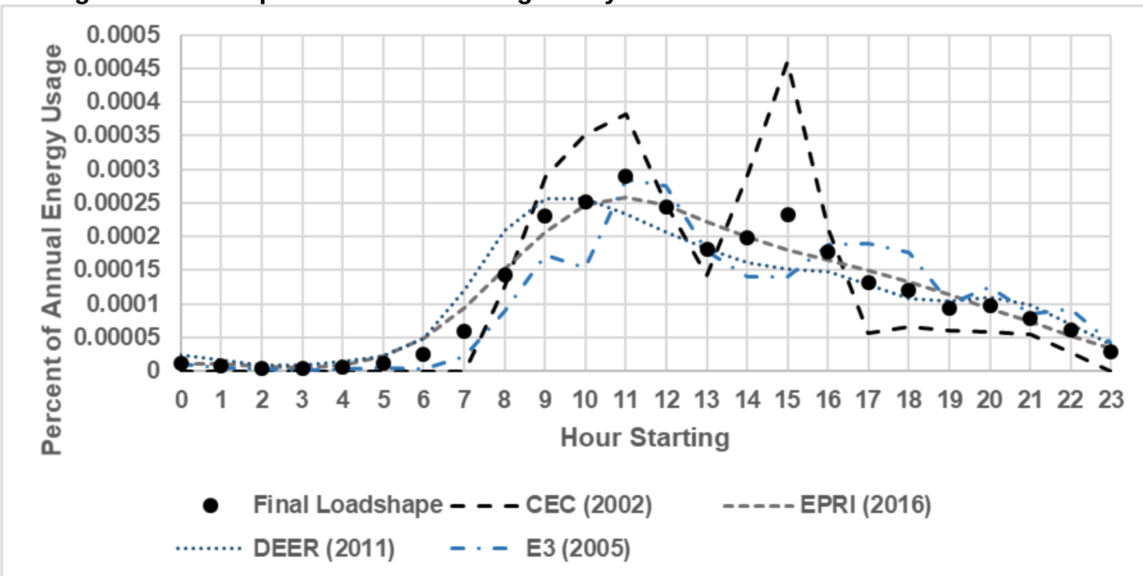
Figure 104: Comparison of the Average Daily Weekday Profile in Winter for Washer



A comparison of the average daily load shape in weekdays in winter for the washer end-use as predicted by the Energy Commission (2002), EPRI (2016), DEER (Itron, Inc. 2011), and E3 (2005).

Source: ADM Associates, Inc.

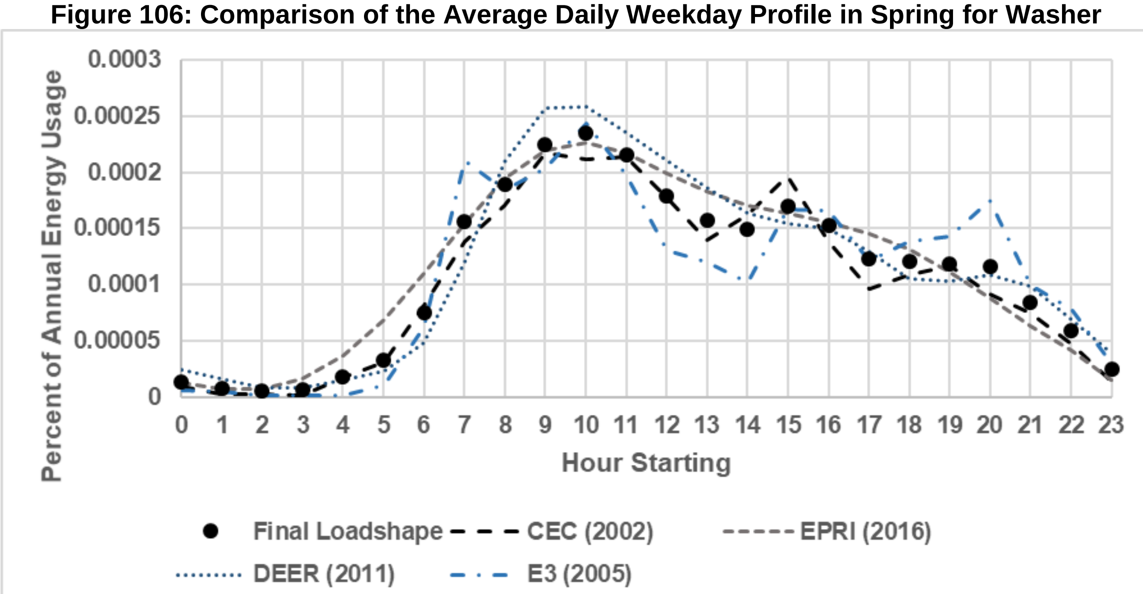
Figure 105: Comparison of the Average Daily Weekend Profile in Winter for Washer



A comparison of the average daily load shape in weekends in winter for the washer end-use as predicted by the Energy Commission (2002), EPRI (2016), DEER (Itron, Inc. 2011), and E3 (2005).

Source: ADM Associates, Inc.

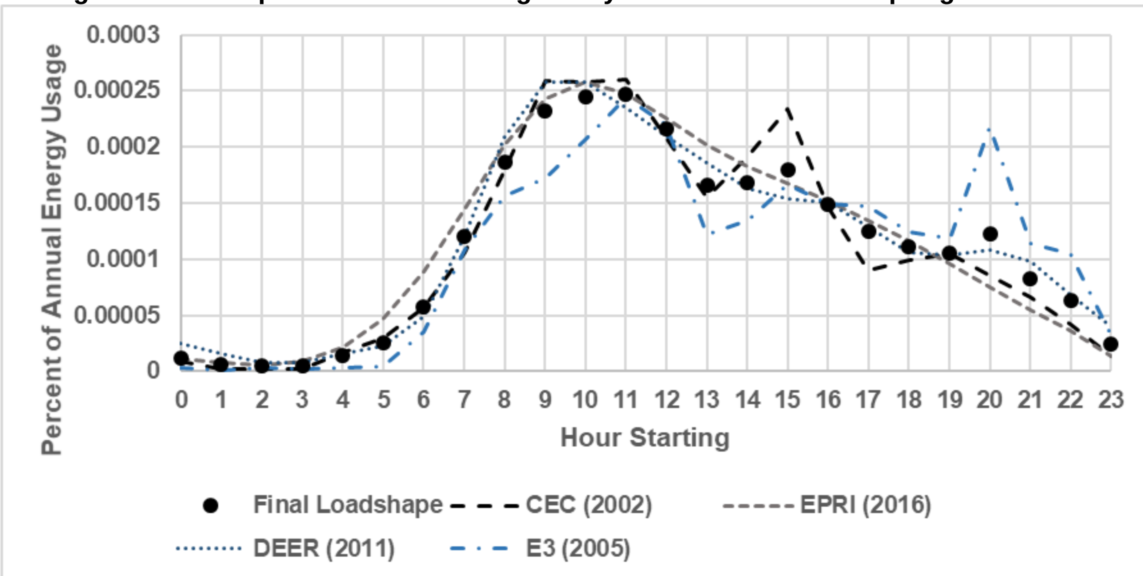
Figure 106: Comparison of the Average Daily Weekday Profile in Spring for Washer



A comparison of the average daily load shape in weekdays in spring for the washer end-use as predicted by the Energy Commission (2002), EPRI (2016), DEER (Itron, Inc. 2011), and E3 (2005).

Source: ADM Associates, Inc.

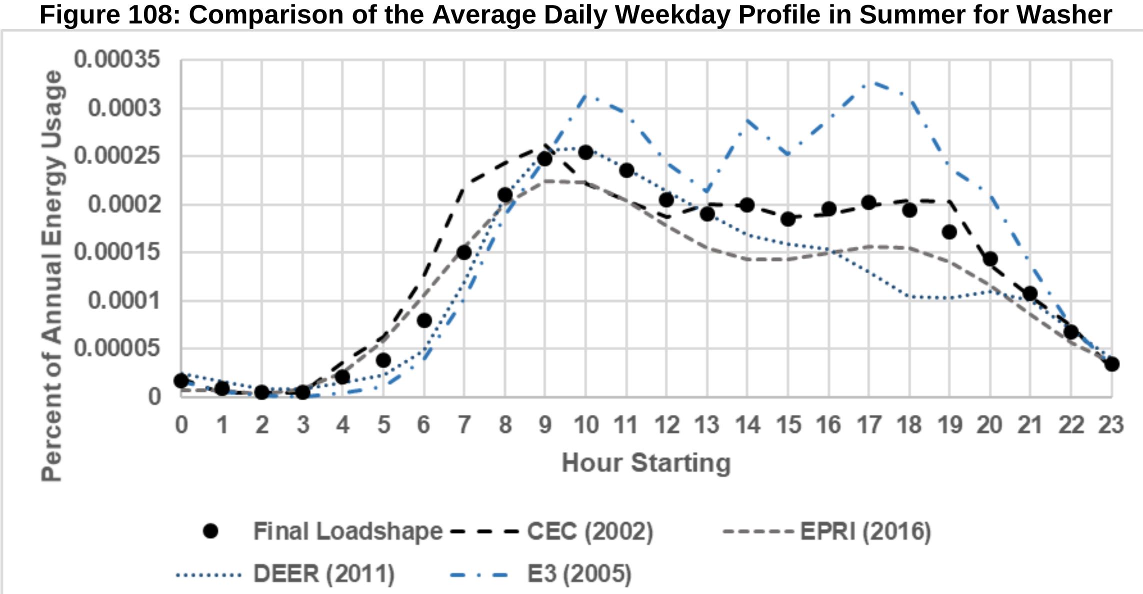
Figure 107: Comparison of the Average Daily Weekend Profile in Spring for Washer



A comparison of the average daily load shape in weekends in spring for the washer end-use as predicted by the Energy Commission (2002), EPRI (2016), DEER (Itron, Inc. 2011), and E3 (2005).

Source: ADM Associates, Inc.

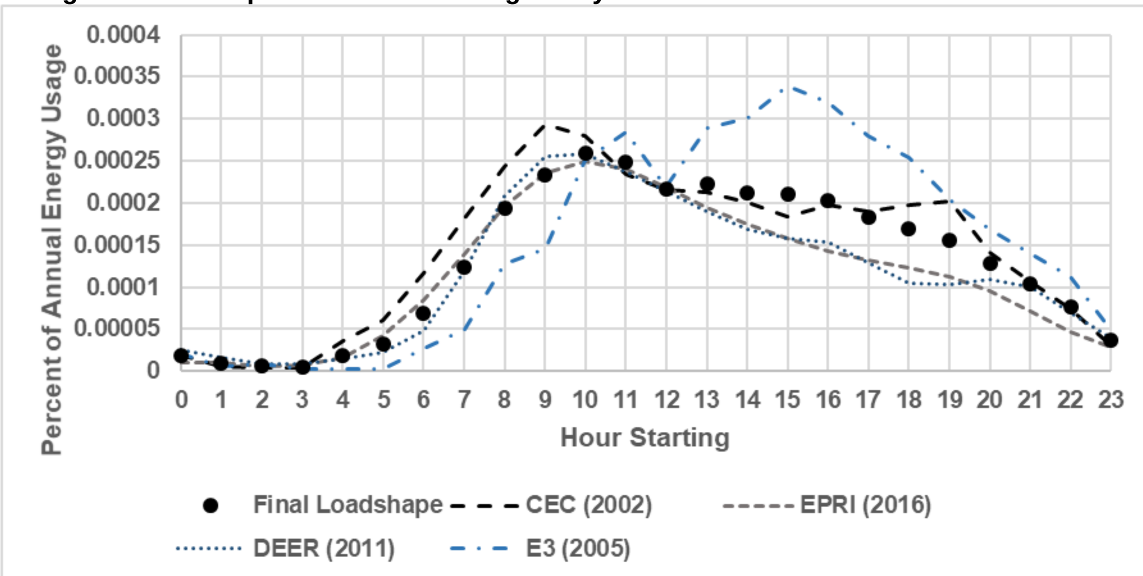
Figure 108: Comparison of the Average Daily Weekday Profile in Summer for Washer



A comparison of the average daily load shape in weekdays in summer for the washer end-use as predicted by the Energy Commission (2002), EPRI (2016), DEER (Itron, Inc. 2011), and E3 (2005).

Source: ADM Associates, Inc.

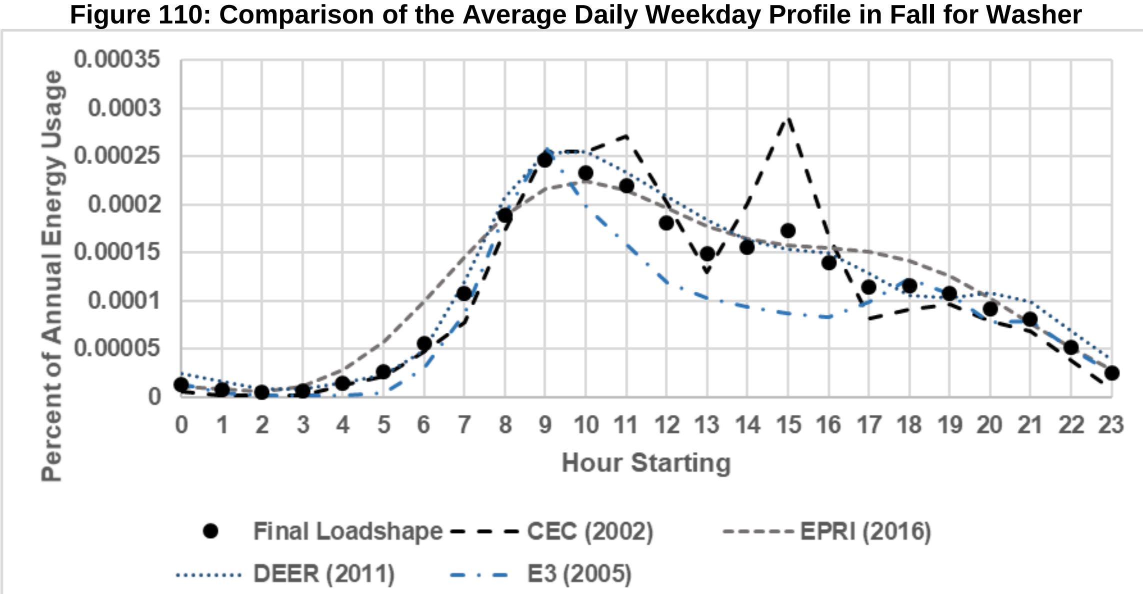
Figure 109: Comparison of the Average Daily Weekend Profile in Summer for Washer



A comparison of the average daily load shape in weekends in summer for the washer end-use as predicted by the Energy Commission (2002), EPRI (2016), DEER (Itron, Inc. 2011), and E3 (2005).

Source: ADM Associates, Inc.

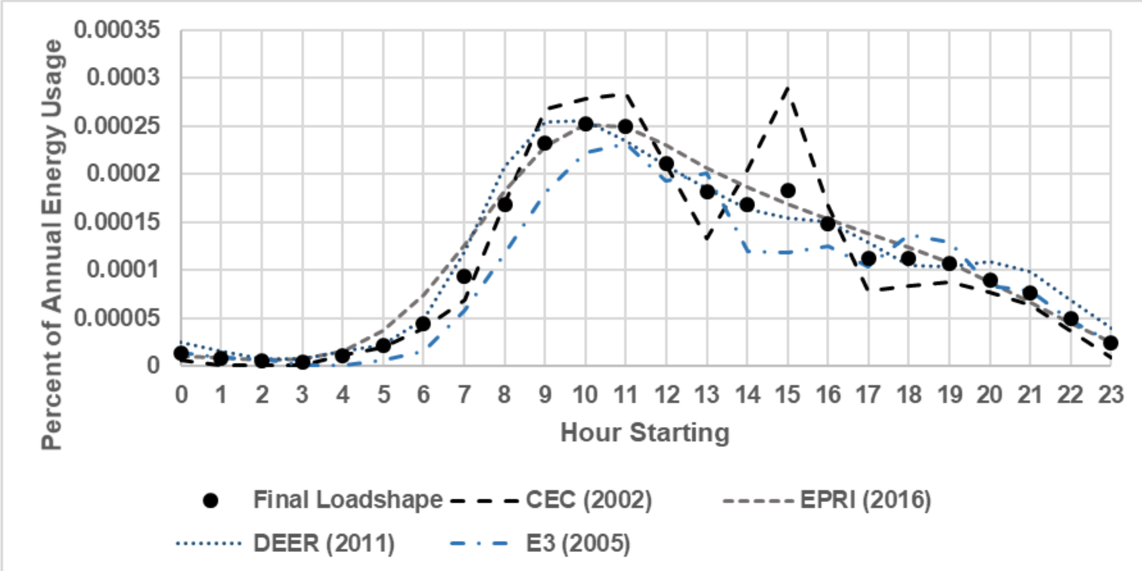
Figure 110: Comparison of the Average Daily Weekday Profile in Fall for Washer



A comparison of the average daily load shape in weekdays in fall for the washer end-use as predicted by the Energy Commission (2002), EPRI (2016), DEER (Itron, Inc. 2011), and E3 (2005).

Source: ADM Associates, Inc.

Figure 111: Comparison of the Average Daily Weekend Profile in Fall for Washer



A comparison of the average daily load shape in weekends in fall for the washer end-use as predicted by the Energy Commission (2002), EPRI (2016), DEER (Itron, Inc. 2011), and E3 (2005).

Source: ADM Associates, Inc.

Water Heating: Clothes Washer

The Energy Commission currently separates the water heating attributable to clothes washing from other forms of water heating. ADM assumed that this load shape is completely synonymous to the load shape for washers and therefore used that load shape for water heating – clothes washer.

Water Heating: Dishwasher

The Energy Commission currently separates the water heating attributable to dishwashing from other forms of water heating. ADM assumed that this load shape is completely synonymous to the load shape for dishwashers and therefore used that load shape for water heating – dishwasher.

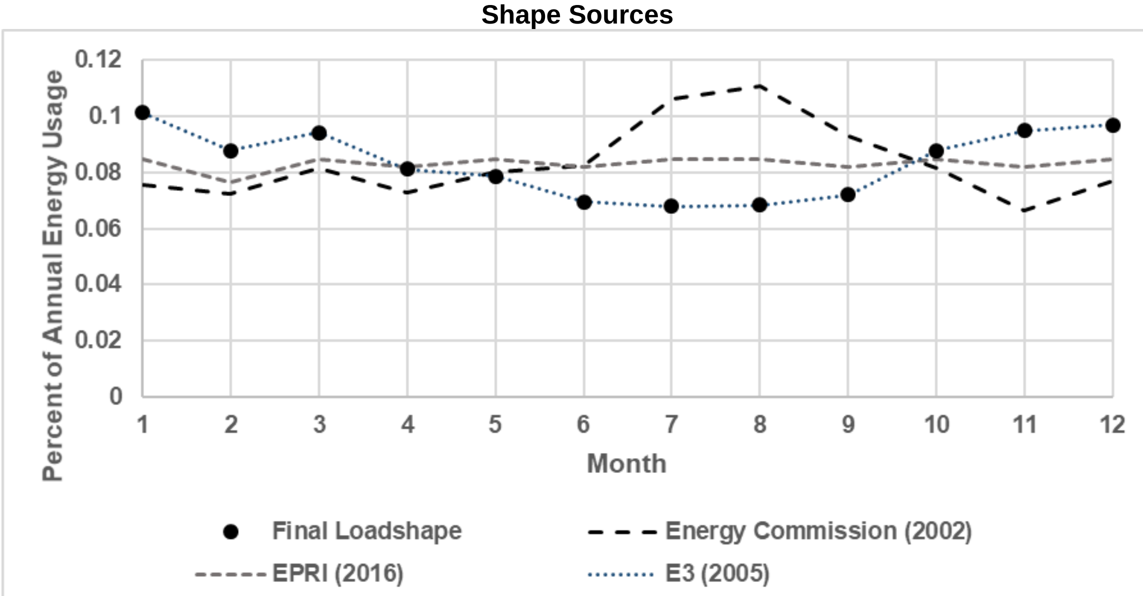
Water Heating: Other

The Energy Commission distinguishes between the water heating attributable to clothes washing, the water heating attributable to dishwashing, and all other forms of water heating. Water heating as modeled through most sources, however, do not currently make this distinction. The load shape from the Energy Commission's 2002 revision also currently includes the water heating for all three forms of water heating embedded in the 8,760-hour load shape. ADM began the process of creating a water heating – other load shape by first reviewing currently available sources for water heating load shapes. After doing so, the team subtracted out the water heating attributable to clothes washing and dishwashing from the overall water heating profile to generate a water heating – other profile.

ADM reviewed three sources for water heating load shapes: the Energy Commission's 2002 load shapes, the EPRI Load Shape Library 4.0 (2016), and the E3 Energy Efficiency Calculator (2005). After reviewing the three data sources, the team ultimately determined that the E3 Energy Efficiency Calculator (2005) appeared to be the most consistent with expected behavior for water heating. Specifically, the E3 Energy Efficiency Calculator load shape showed a reduction in energy usage in the warmer season—which should be expected as less heat is lost due to transmission and the starting temperature for water being heated is higher. Therefore, ADM elected to use the E3 (2005) profile in the models. Figure 112 through

Figure 129 show the comparison between all three data sources for multifamily and single-family homes.

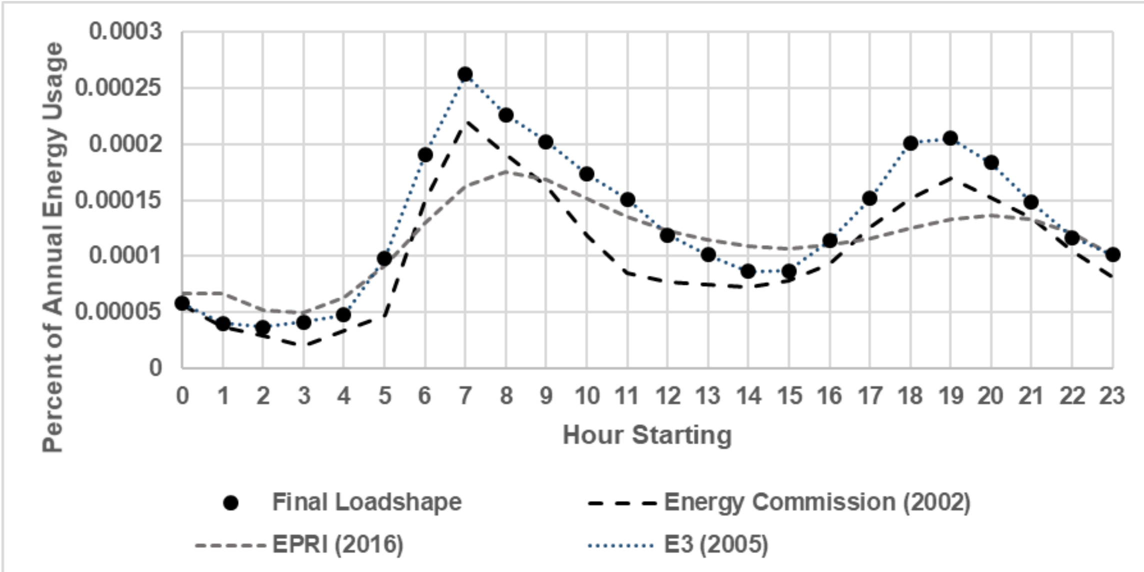
Figure 112: Comparison of Monthly Energy Usage for Multifamily Water Heater Load Shape Sources



A comparison of the monthly energy usage for the multifamily water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

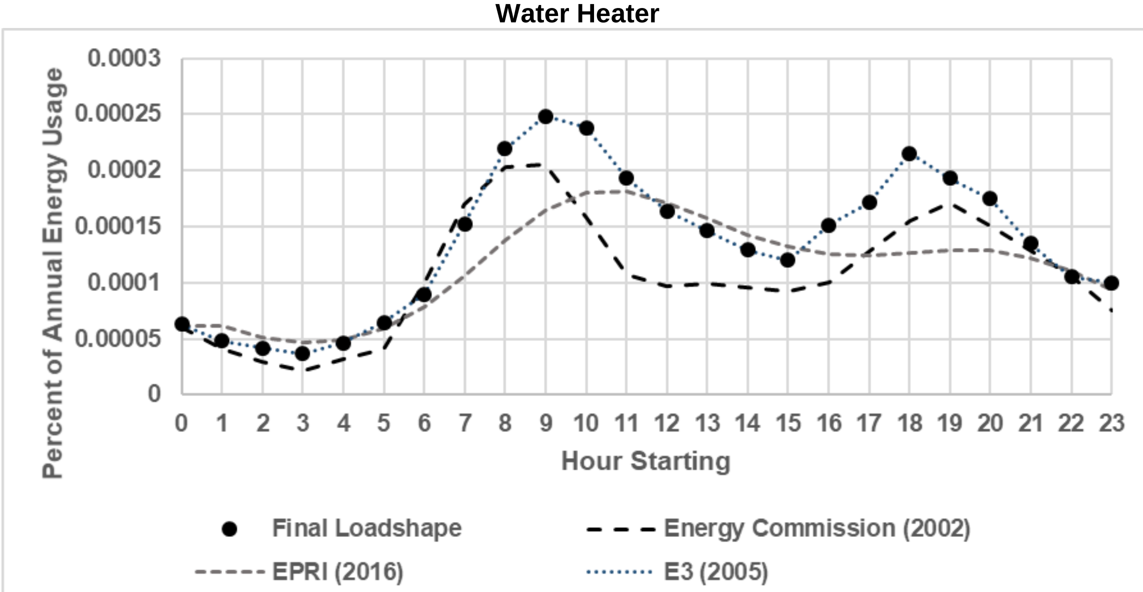
Figure 113: Comparison of the Average Daily Weekday Profile in Winter for Multifamily Water Heater



A comparison of the average daily load shape in weekdays in winter for the multifamily water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

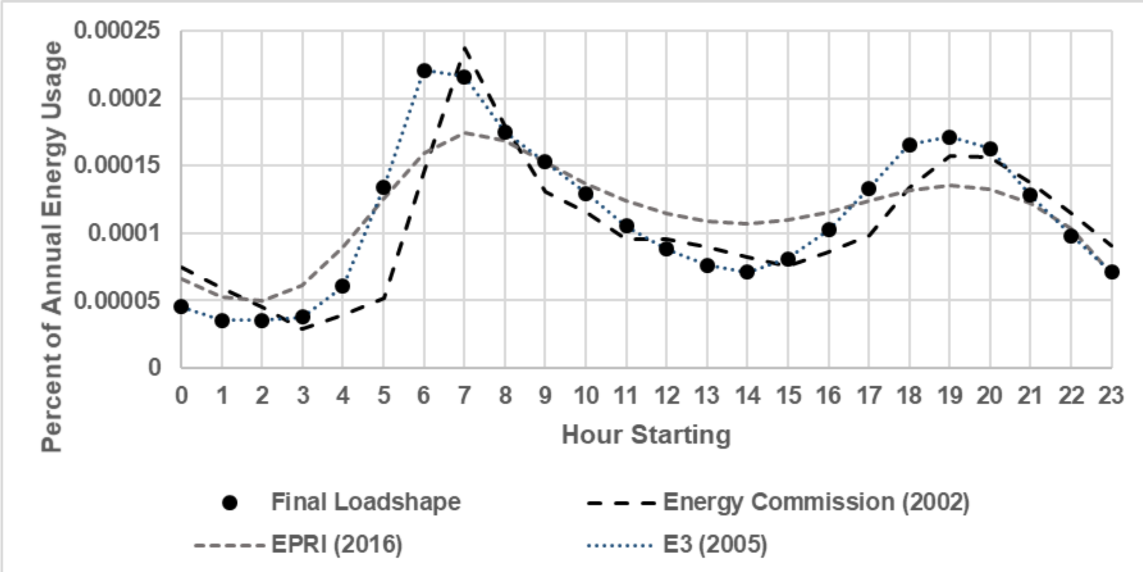
Figure 114: Comparison of the Average Daily Weekend Profile in Winter for Multifamily Water Heater



A comparison of the average daily load shape in weekends in winter for the multifamily water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

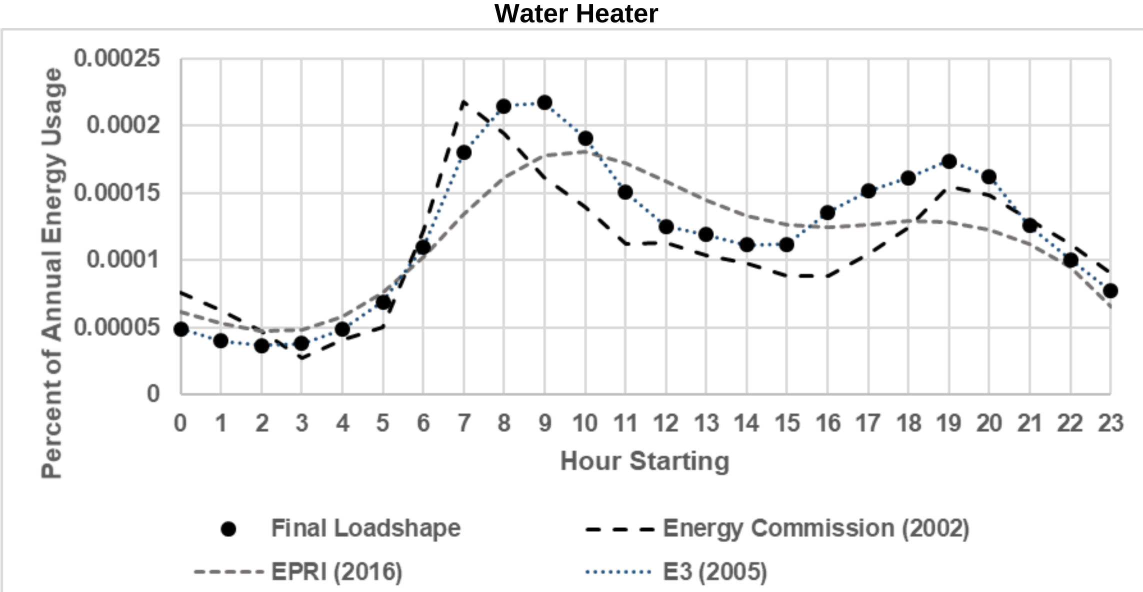
Figure 115: Comparison of the Average Daily Weekday Profile in Spring for Multifamily Water Heater



A comparison of the average daily load shape in weekdays in spring for the multifamily water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

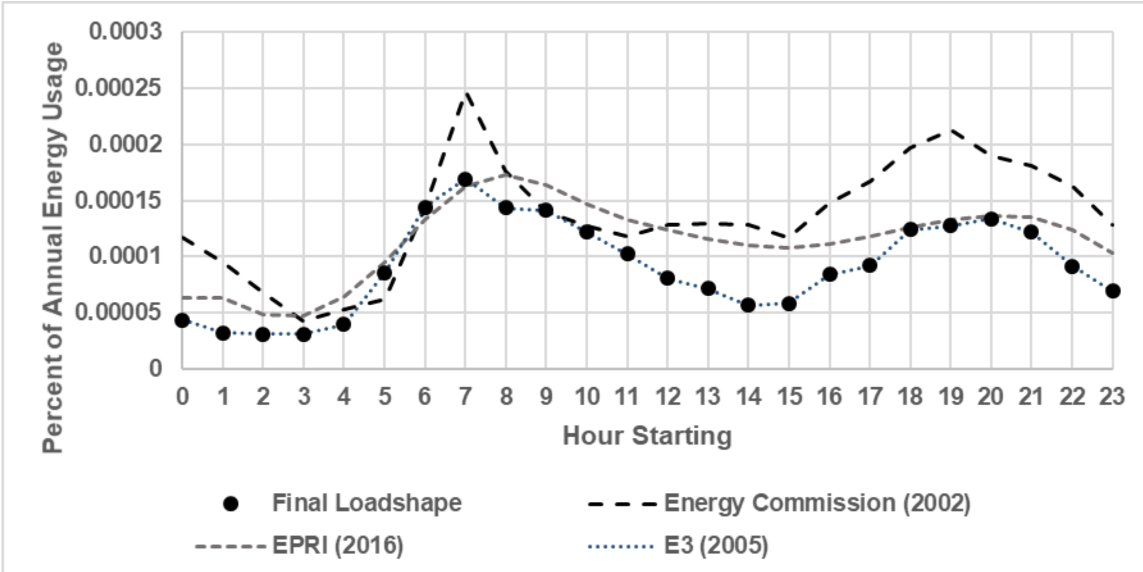
Figure 116: Comparison of the Average Daily Weekend Profile in Spring for Multifamily Water Heater



A comparison of the average daily load shape in weekends in spring for the multifamily water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

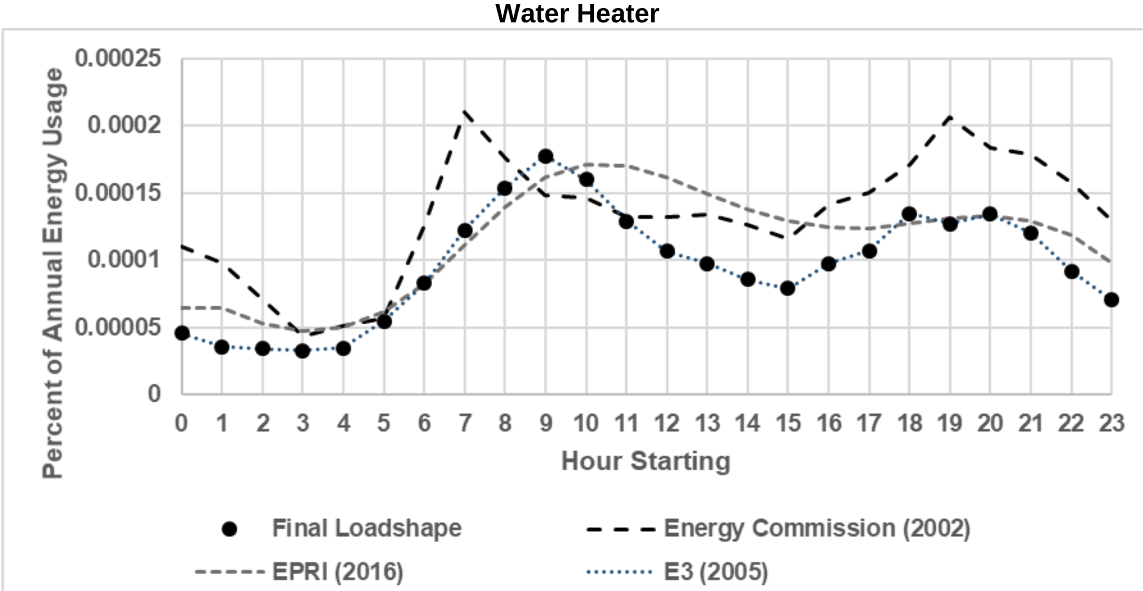
Figure 117: Comparison of the Average Daily Weekday Profile in Summer for Multifamily Water Heater



A comparison of the average daily load shape in weekdays in summer for the multifamily water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

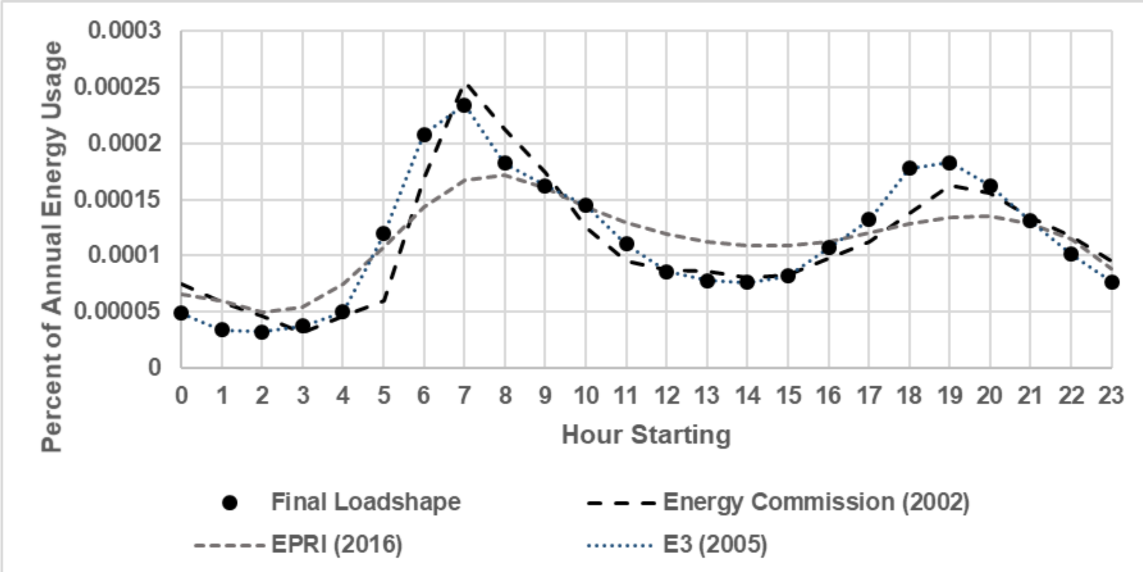
Figure 118: Comparison of the Average Daily Weekend Profile in Summer for Multifamily Water Heater



A comparison of the average daily load shape in weekends in summer for the multifamily water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

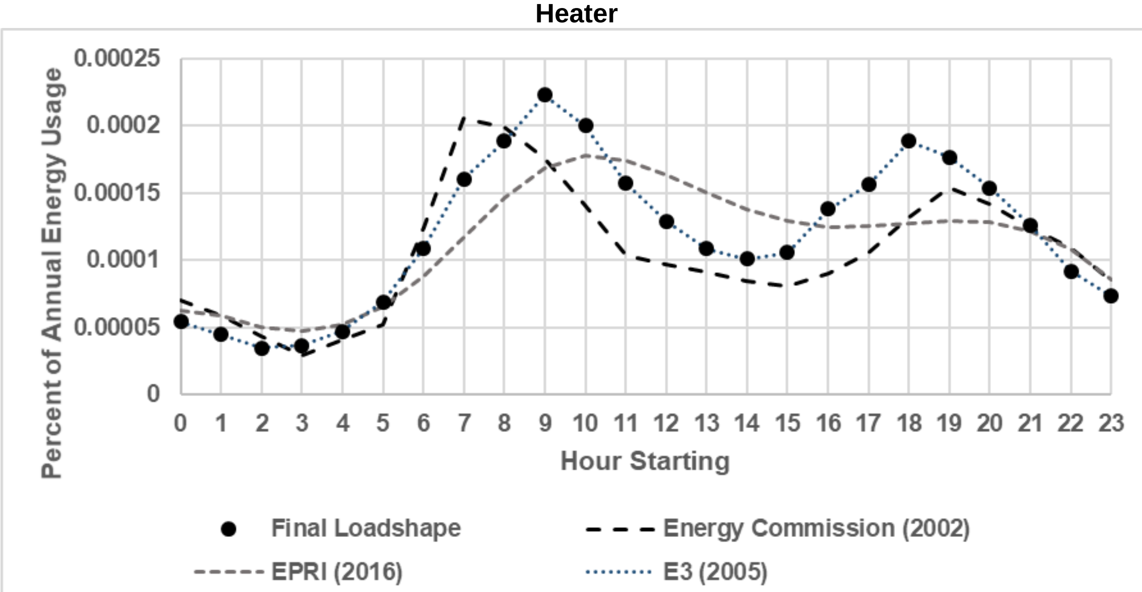
Figure 119: Comparison of the Average Daily Weekday Profile in Fall for Multifamily Water Heater



A comparison of the average daily load shape in weekdays in fall for the multifamily water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

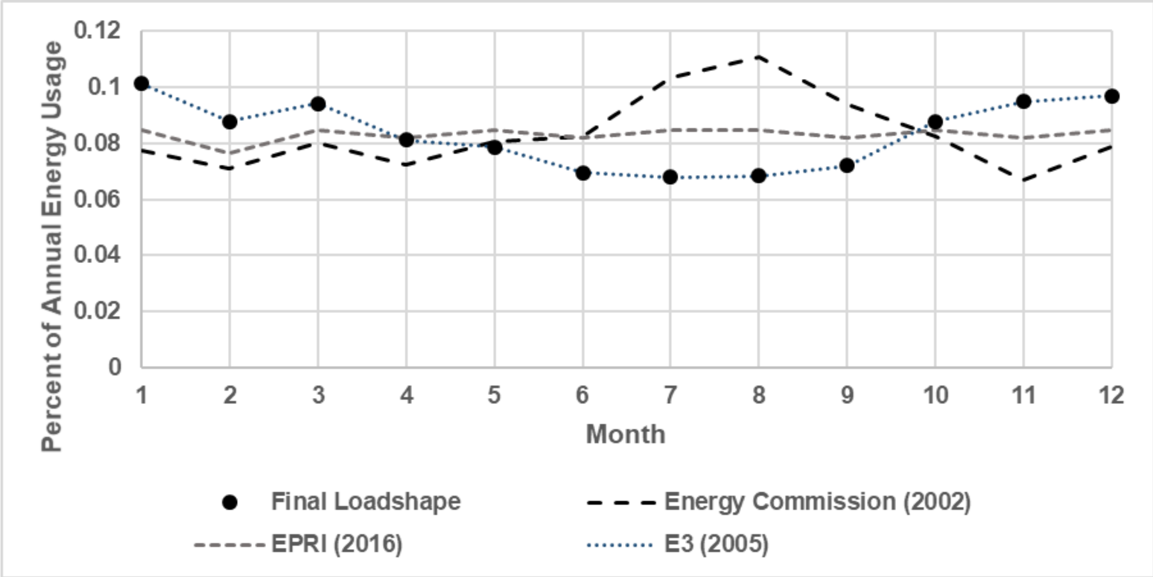
Figure 120: Comparison of the Average Daily Weekend Profile in Fall for Multifamily Water Heater



A comparison of the average daily load shape in weekends in fall for the multifamily water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

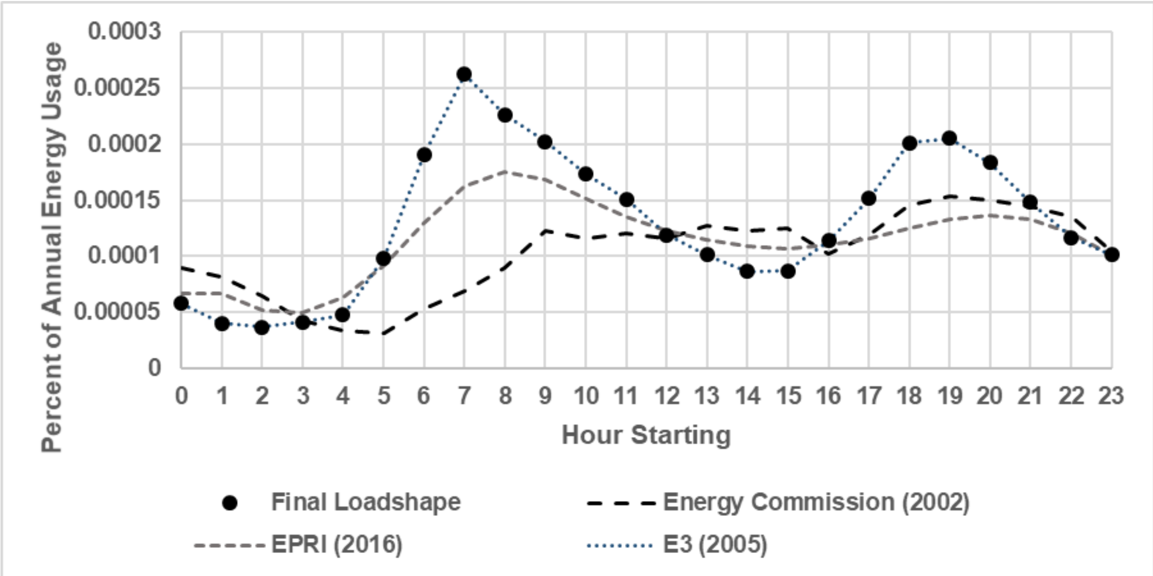
Figure 121: Comparison of Monthly Energy Usage for Single-Family Water Heater Load Shape Sources



A comparison of the monthly energy usage for the single-family water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

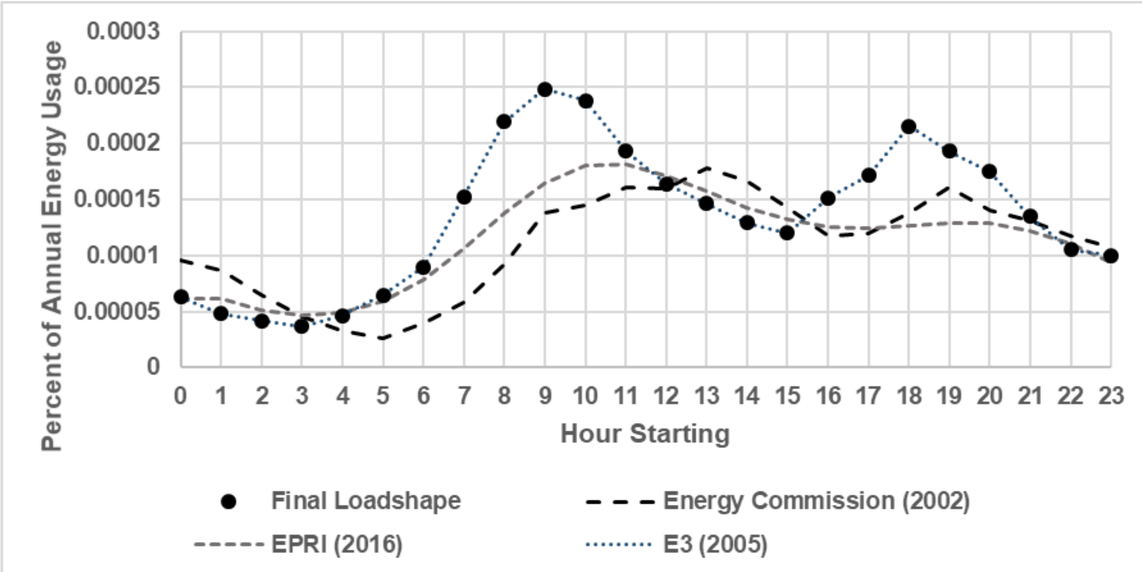
Figure 122: Comparison of the Average Daily Weekday Profile in Winter for Single-Family Water Heater



A comparison of the average daily load shape in weekdays in winter for the single-family water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

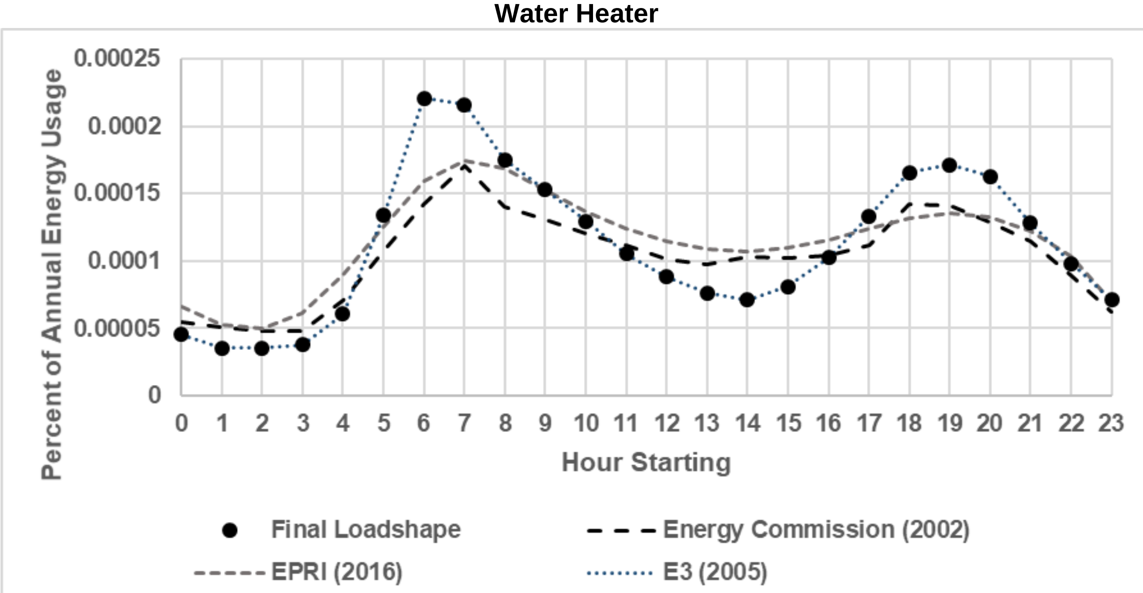
Figure 123: Comparison of the Average Daily Weekend Profile in Winter for Single-Family Water Heater



A comparison of the average daily load shape in weekends in winter for the single-family water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

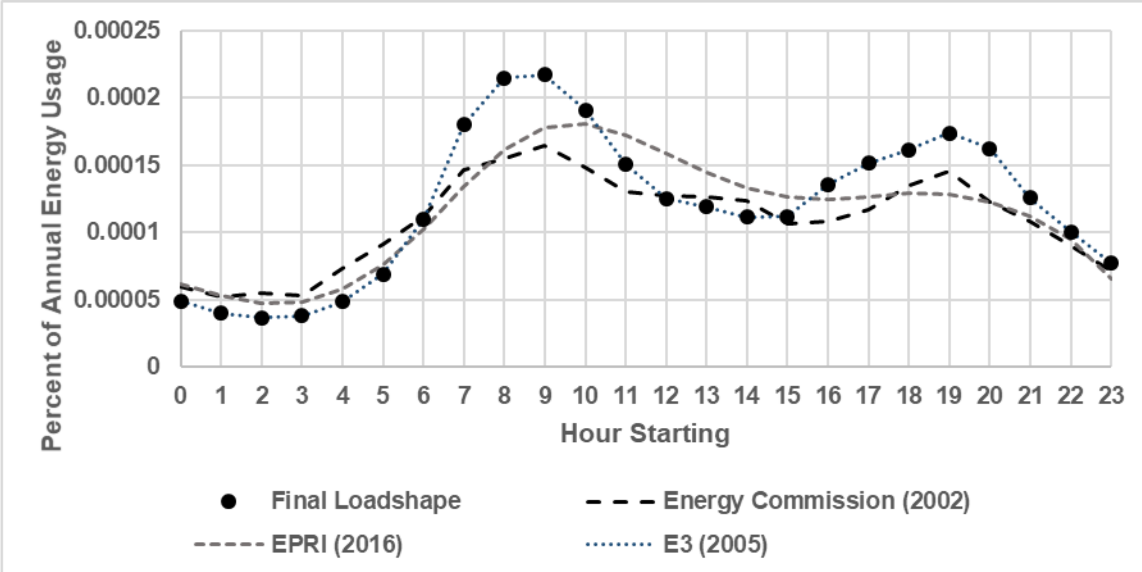
Figure 124: Comparison of the Average Daily Weekday Profile in Spring for Single-Family Water Heater



A comparison of the average daily load shape in weekdays in spring for the single-family water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

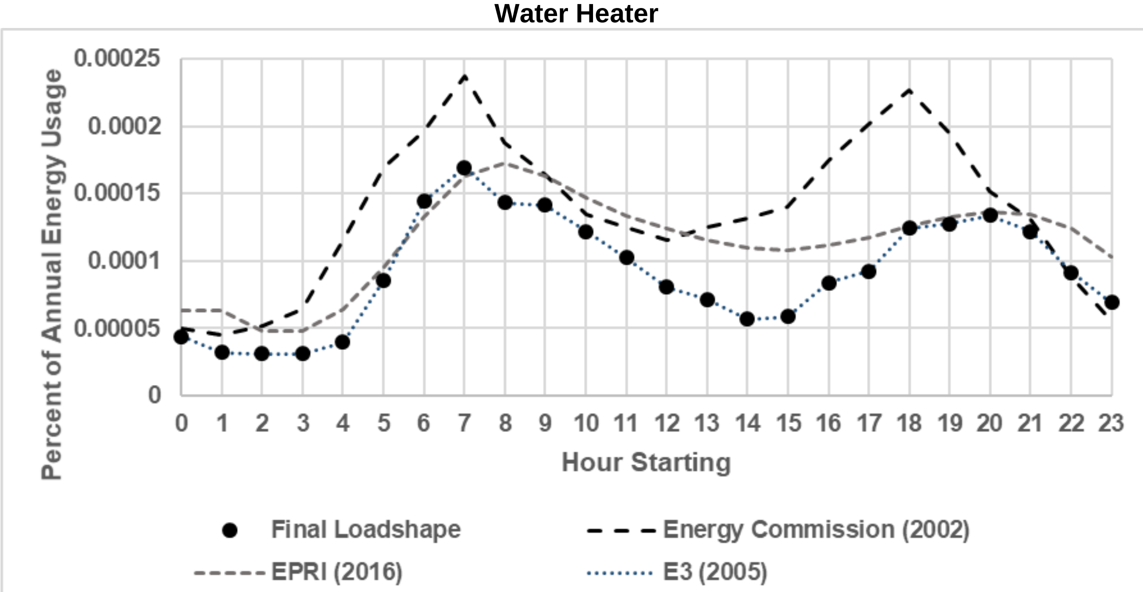
Figure 125: Comparison of the Average Daily Weekend Profile in Spring for Single-Family Water Heater



A comparison of the average daily load shape in weekends in spring for the single-family water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

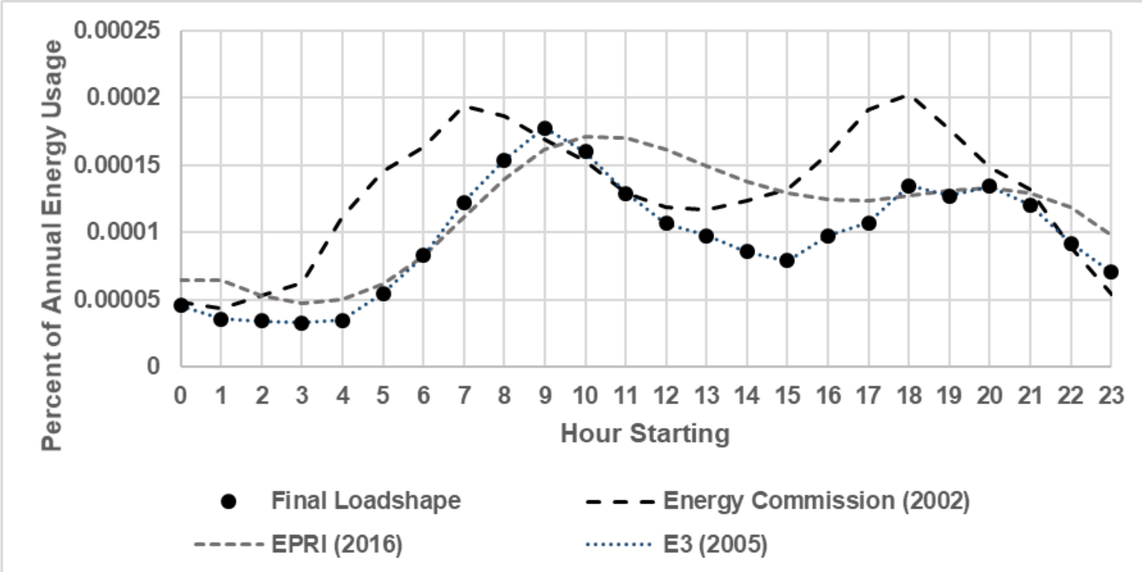
Figure 126: Comparison of the Average Daily Weekday Profile in Summer for Single-Family Water Heater



A comparison of the average daily load shape in weekdays in summer for the single-family water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

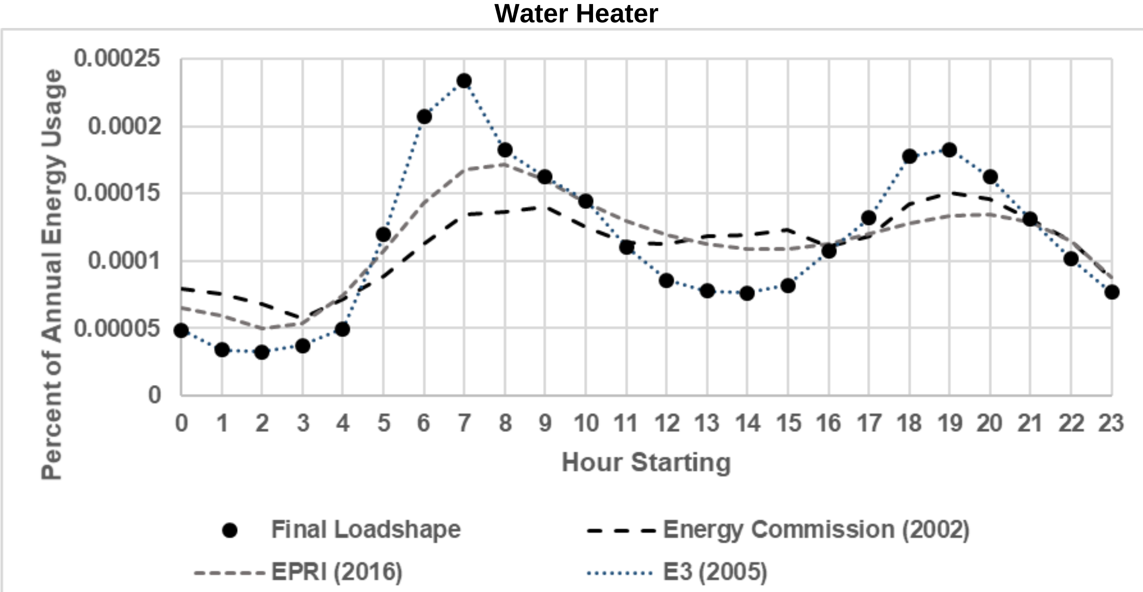
Figure 127: Comparison of the Average Daily Weekend Profile in Summer for Single-Family Water Heater



A comparison of the average daily load shape in weekends in summer for the single-family water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

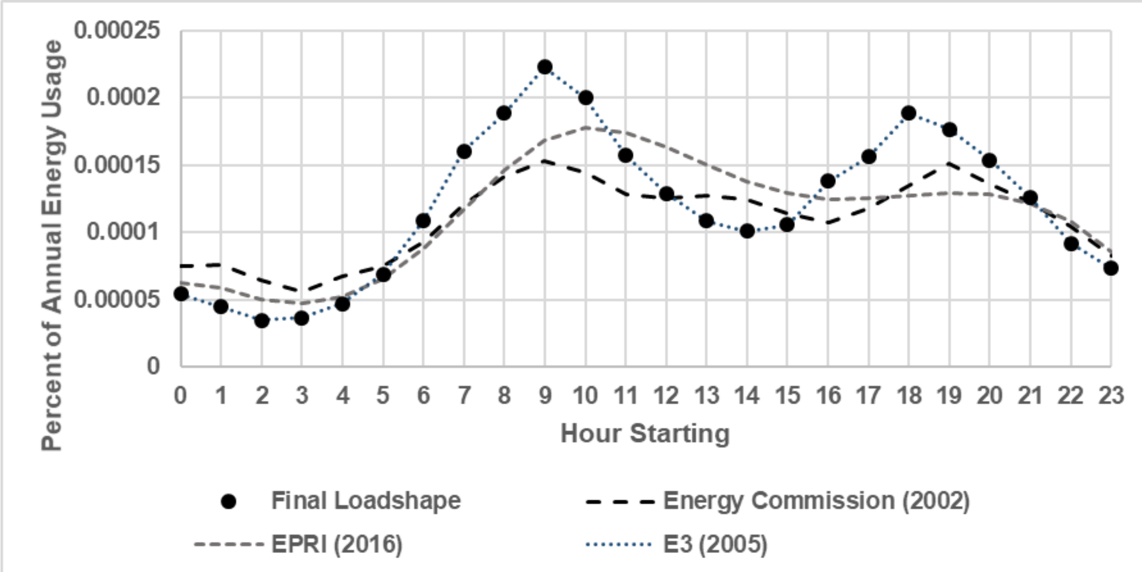
Figure 128: Comparison of the Average Daily Weekday Profile in Fall for Single-Family Water Heater



A comparison of the average daily load shape in weekdays in fall for the single-family water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

Figure 129: Comparison of the Average Daily Weekend Profile in Fall for Single-Family Water Heater



A comparison of the average daily load shape in weekends in fall for the single-family water heater end-use as predicted by the Energy Commission's 2002 load shapes, EPRI (2016), and E3 (2005).

Source: ADM Associates, Inc.

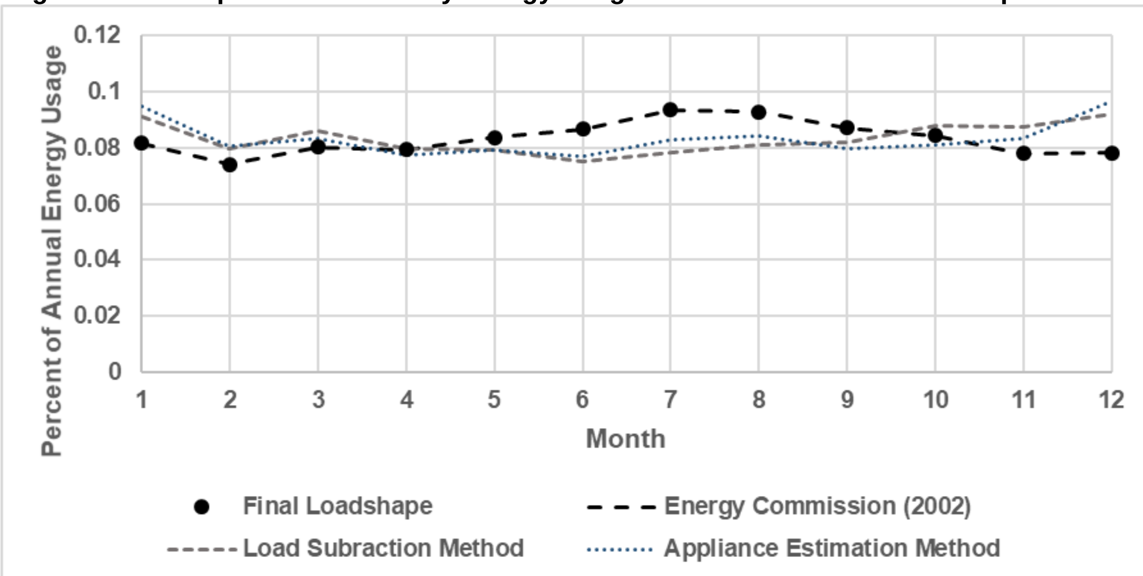
Miscellaneous

The miscellaneous end-use represents all residential electric energy usage that is not currently captured by the other end-uses. In general, this end-use is specific to the Energy Commission, as other studies that may capture a miscellaneous end-use will include end-use loads that are otherwise well-represented by the Energy Commission. To validate the existing miscellaneous load shape, ADM attempted two alternative approaches to creating a new miscellaneous load shape. In the first approach, ADM used the non-HVAC load shapes and the shoulder-season AMI data to subtract out the remaining load once all other end-uses had been disaggregated, assuming a low prevalence of HVAC in that period of interest. In the second approach, ADM used a bottom-up method of approximating all other appliances that were not already represented by the Energy Commission's other end-uses. These appliances included items such as well-pumping, telecommunications, and office equipmen. The Energy Commission's 2002 miscellaneous load shape resembled the average of the two original approaches. Given no other potential sources for a miscellaneous load shape, ADM used the Energy Commission's 2002 load shape in the residential models.

Figure 130 through

Figure 138 present the comparison of load shapes at a monthly and average daily by season level.

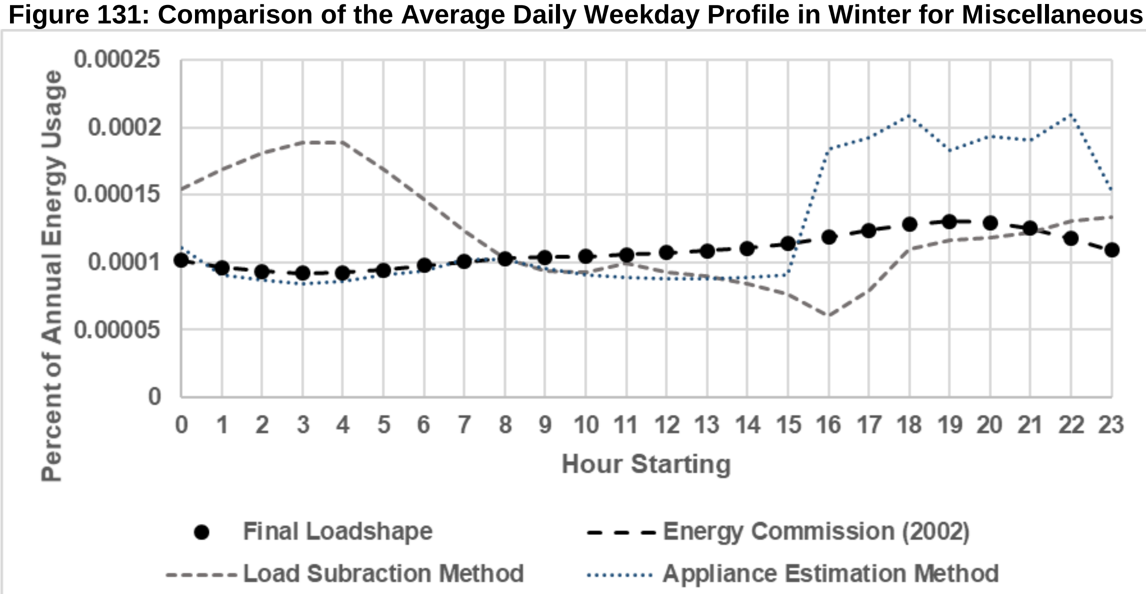
Figure 130: Comparison of Monthly Energy Usage for Miscellaneous Load Shape Sources



A comparison of the monthly energy usage for the miscellaneous end-use as predicted by the 2002 Energy Commission load shape and the two original load shapes.

Source: ADM Associates, Inc.

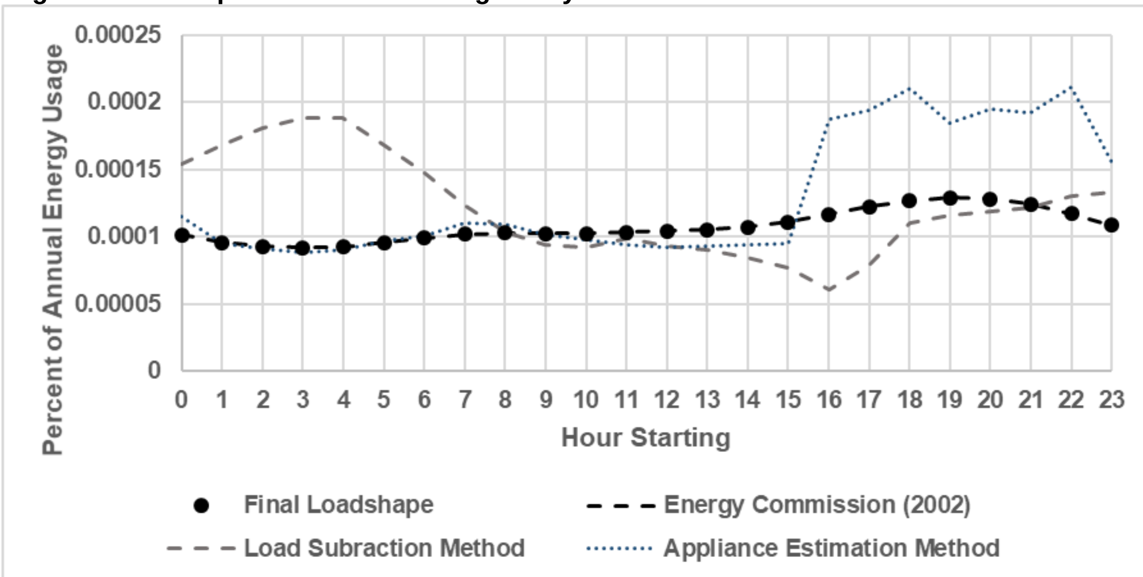
Figure 131: Comparison of the Average Daily Weekday Profile in Winter for Miscellaneous



A comparison of the average daily load shape in weekdays in winter for the miscellaneous end-use as predicted by the 2002 Energy Commission load shape and the two original load shapes.

Source: ADM Associates, Inc.

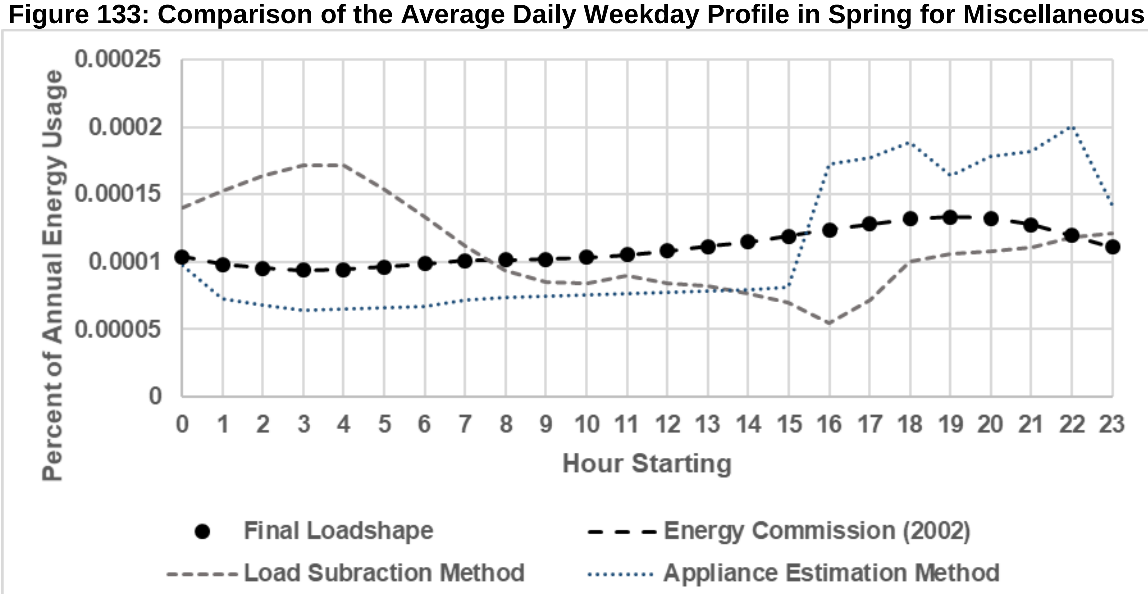
Figure 132: Comparison of the Average Daily Weekend Profile in Winter for Miscellaneous



A comparison of the average daily load shape in weekends in winter for the miscellaneous end-use as predicted by the 2002 Energy Commission load shape and the two original load shapes.

Source: ADM Associates, Inc.

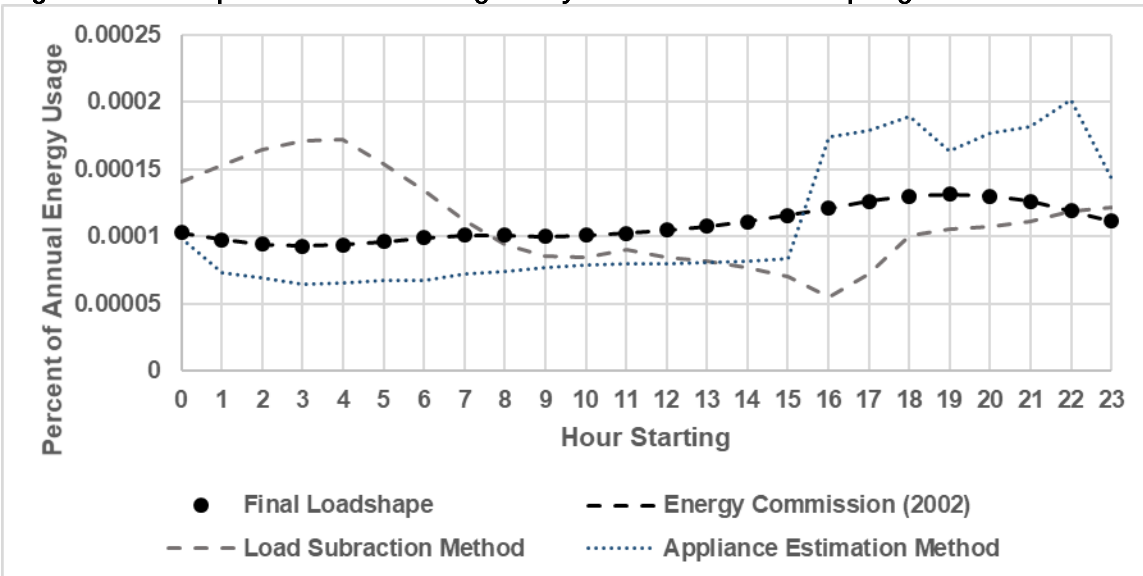
Figure 133: Comparison of the Average Daily Weekday Profile in Spring for Miscellaneous



A comparison of the average daily load shape in weekdays in spring for the miscellaneous end-use as predicted by the 2002 Energy Commission load shape and the two original load shapes.

Source: ADM Associates, Inc.

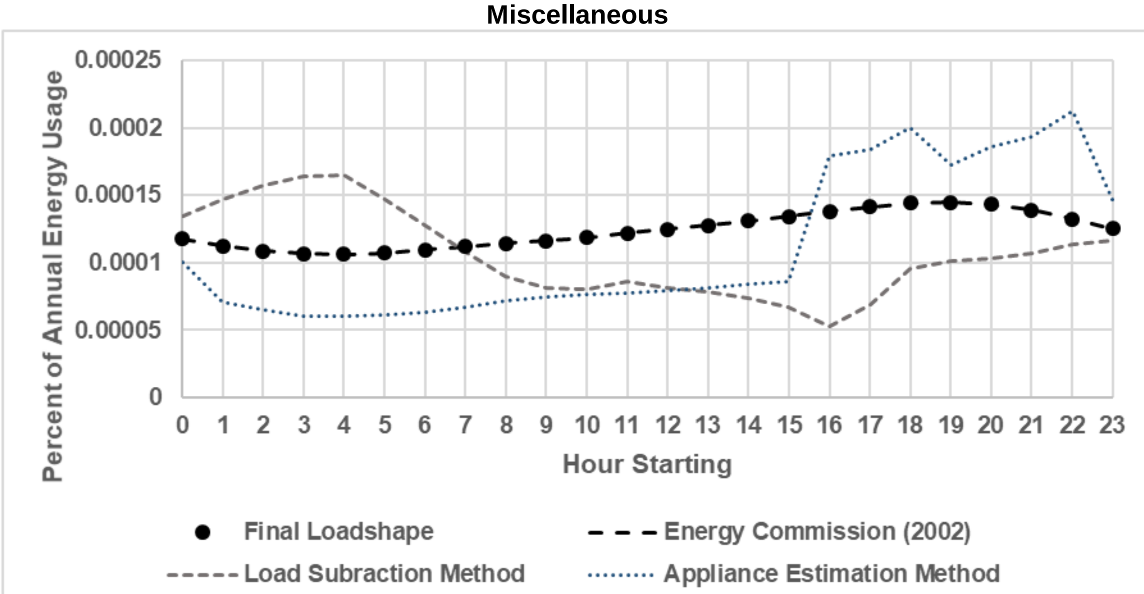
Figure 134: Comparison of the Average Daily Weekend Profile in Spring for Miscellaneous



A comparison of the average daily load shape in weekends in spring for the miscellaneous end-use as predicted by the 2002 Energy Commission load shape and the two original load shapes.

Source: ADM Associates, Inc.

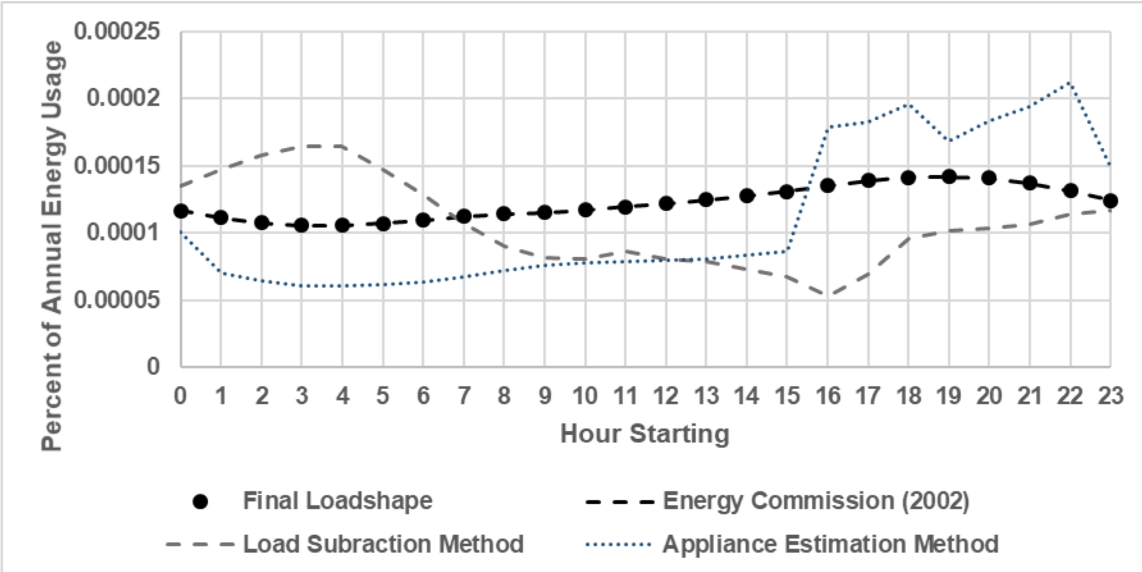
Figure 135: Comparison of the Average Daily Weekday Profile in Summer for Miscellaneous



A comparison of the average daily load shape in weekdays in summer for the miscellaneous end-use as predicted by the 2002 Energy Commission load shape and the two original load shapes.

Source: ADM Associates, Inc.

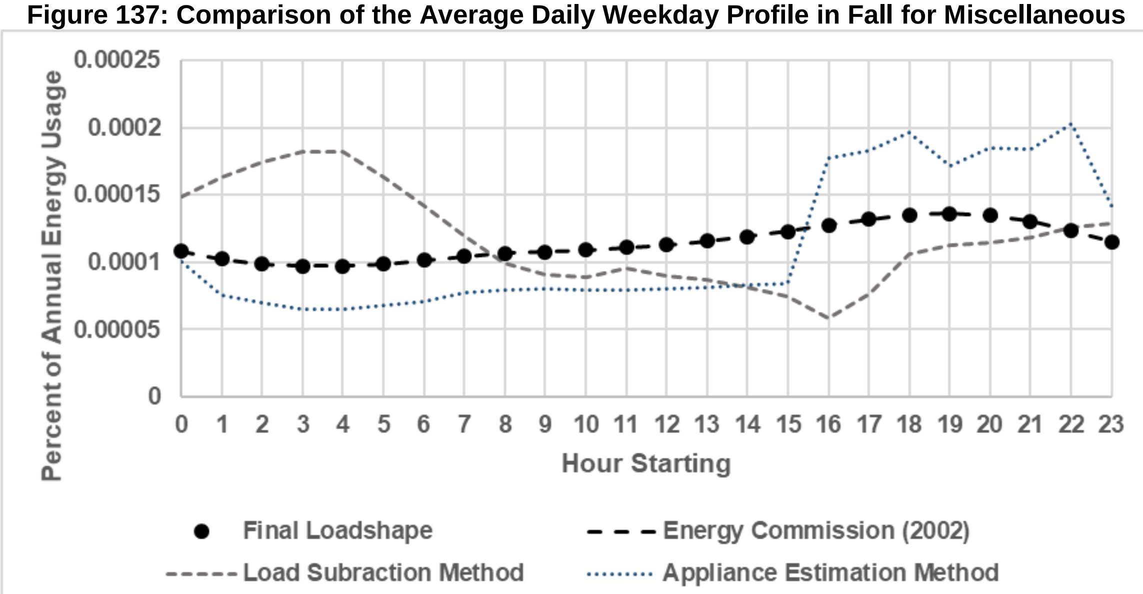
Figure 136: Comparison of the Average Daily Weekend Profile in Summer for Miscellaneous



A comparison of the average daily load shape in weekends in summer for the miscellaneous end-use as predicted by the 2002 Energy Commission load shape and the two original load shapes.

Source: ADM Associates, Inc.

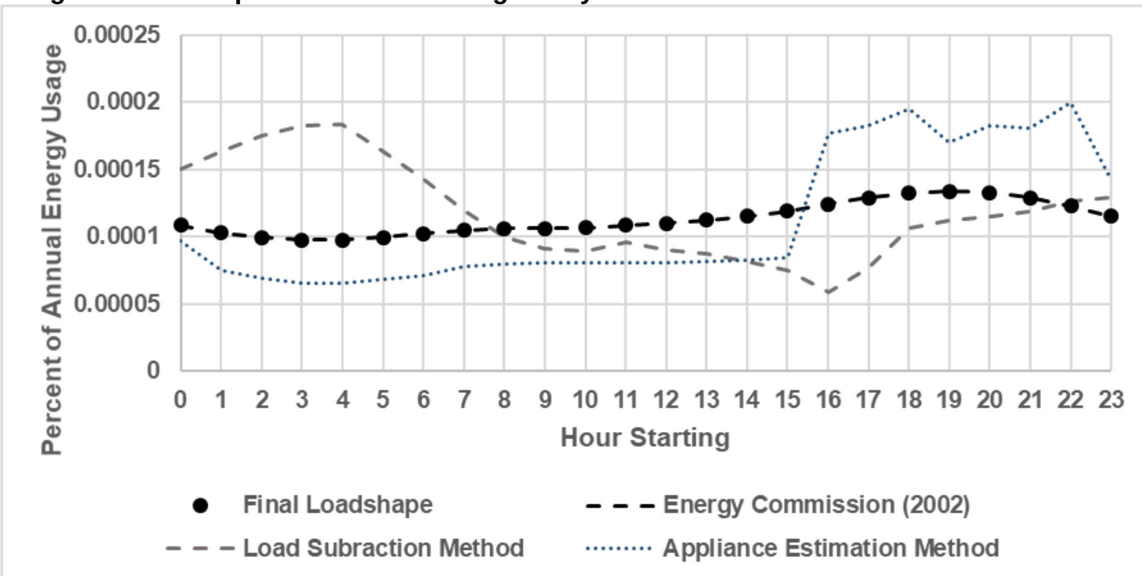
Figure 137: Comparison of the Average Daily Weekday Profile in Fall for Miscellaneous



A comparison of the average daily load shape in weekdays in fall for the miscellaneous end-use as predicted by the 2002 Energy Commission load shape and the two original load shapes.

Source: ADM Associates, Inc.

Figure 138: Comparison of the Average Daily Weekend Profile in Fall for Miscellaneous



A comparison of the average daily load shape in weekends in fall for the miscellaneous end-use as predicted by the 2002 Energy Commission load shape and the two original load shapes.

Source: ADM Associates, Inc.

Cooling

Cooling and heating load shapes for the residential sector were developed using an analytical model as opposed to using EnergyPlus to simulate the load shape. Residential cooling and heating can be distinctly detected in AMI data as they tend to function as on/off without overlapping with one another and with distinct periods over a calendar year in which it is highly likely that neither end-use is being used. Therefore, ADM used an approach that aimed to accomplish the following:

- Determine at what outdoor air temperature HVAC does not occur for weekends and weekdays
- Isolate the average daily load shape for the days in which no HVAC occurs
- Subtract the base load shape from the average daily load shape at every other temperature value present in the data set to create HVAC load shapes at each temperature, assuming temperatures below the determined balance point represent heating and temperatures above the determined balance point represent cooling
- Determine, from the average daily load at the available temperatures, the relationship between weather and the total daily energy usage for heating and cooling. Because temperatures in future years may fall outside the temperature bands of the 2014-2015 data set, determining the relationship between temperature and daily energy use allows ADM to predict the daily energy use for heating or cooling on days that extend beyond the historical temperature exhibited during 2014-2015.

To determine at what outdoor air temperature HVAC does not occur, ADM first calculated the average daily air temperature for each day. The average daily air temperature was then rounded to the nearest two degrees. By rounding the average daily air temperature in this manner, the number of potential data points at each temperature bin is increased, therefore reducing the potential of falsely detecting a balance point due to a lack of representative points at that given temperature. After calculating the rounded temperature bins, the average daily load shape is then generated by taking the average load at each hour across all days belonging to that temperature bin. By calculating the average daily load shape, one can reduce the volatility associated with each data point and isolate the typical building load shape at that temperature bin.

After generating the temperature bins and average daily load shape at each temperature bin, the balance point is then calculated by finding the temperature bin with the minimum daily load, as calculated by summing the average daily load at each temperature bin. The average daily load shape belonging to the temperature bin with the minimum daily load shape is then assumed to be the base load shape. Heating and cooling loads are then disaggregated by subtracting the base load values at each hour from the average daily profiles from the remaining temperature bins, creating heating and cooling load shapes at each temperature bin. Temperature bins that fall below the balance point are considered heating temperatures and temperature bins that fall above the balance point are considered cooling temperatures. This process is repeated once for weekdays (Monday through Friday) and once for weekends/holidays (Saturday, Sunday, and holidays).

The load shapes at the varying temperature bins provide some clarity as to how heating and cooling change in shape as temperature changes. However, the extrapolation of these load shapes is limited to the temperature with which the loads are modeled. In this case, temperatures are limited by the observed temperature in 2014 and 2015. To increase the generalizability of the load shapes, ADM decoupled the process of estimating the daily energy usage (relative to the annual energy usage) from the 24-hour profile at each temperature bin. Each 24-hour profile was normalized relative to its daily energy usage, thus resulting in a daily energy usage totaling one per day. Relative daily energy usage is then estimated by approximating the relationship between heating/cooling energy use at various temperatures and HDD and CDD.

To do this, ADM calculated average daily temperatures. Unlike the daily load shapes, ADM rounded the values to the nearest whole number instead of to the nearest two degrees. As the project analysts regress these values in a piecewise regression, this was done to retain data points and prevent potential over-fitting of the regression equation. HDD and CDD were calculated using the balance point, as detected from the daily load shape generation with an adjustment of an additional degree for CDD calculation and less one degree for HDD calculation to account for the two-degree variance of the detected balance point. For each HDD or CDD, the average daily cooling or heating load is calculated by first calculating the average daily energy use at each HDD and CDD as well as at the balance point and then subtracting the base energy use from the balance point days from the energy use at each HDD or CDD.

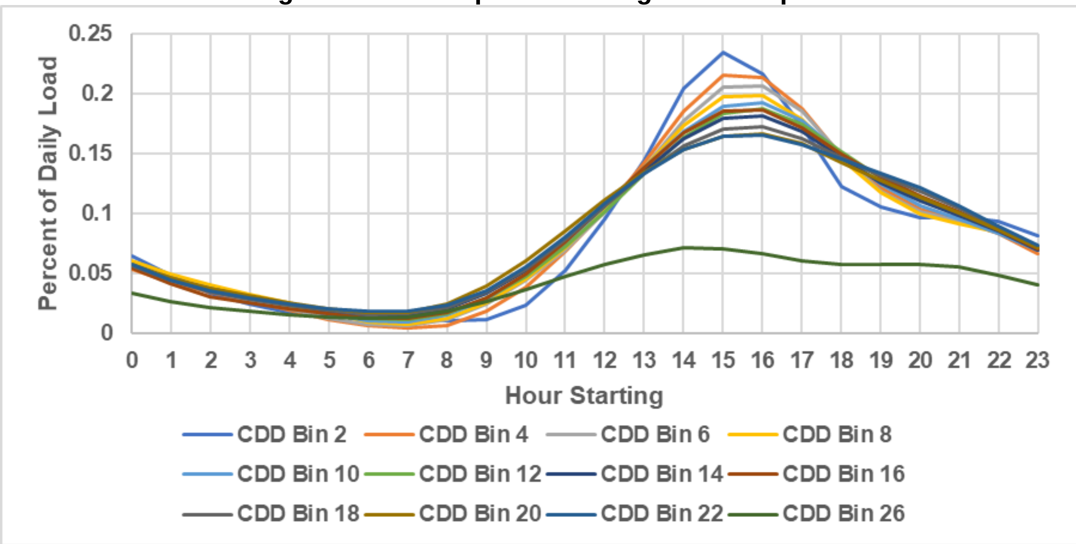
After calculating an estimated heating and cooling daily load at each HDD or CDD, a piecewise linear regression was used to model the load by HDD or CDD, with breakpoints assigned via a visual assessment of the daily load as plotted against the HDD or CDD. The relationship between heating and cooling load and HDD/CDD tends to manifest as a polynomial fit, with flat positive slope for the HDD/CDD closest to zero, steep slope for moderate values, and a declining positive slope as HDD/CDD increase away from the more moderate values. While a cubic polynomial regression could be used to capture this relationship, polynomial fits on limited data points can result in regression coefficients that accurately predict values within the range of values used to generate the model while creating inflated values outside of that range. Therefore, to mitigate this impact, a piecewise linear regression was selected instead.

The heating and cooling loads were ultimately disaggregated and compressed into the following pieces:

- For each 2-degree temperature bin, a heating or cooling 24-hour load shape was stored, normalized to a value of one.
- A balance point was determined, with the CDD base being one degree above the balance point and the HDD base being one degree below the balance point.
- A set of coefficients which, at varying HDD/CDD ranges, can be used to estimate the daily heating and cooling load.

Examples of the cooling load shapes are presented in Figure 139.

Figure 139: Example of Cooling Load Shapes



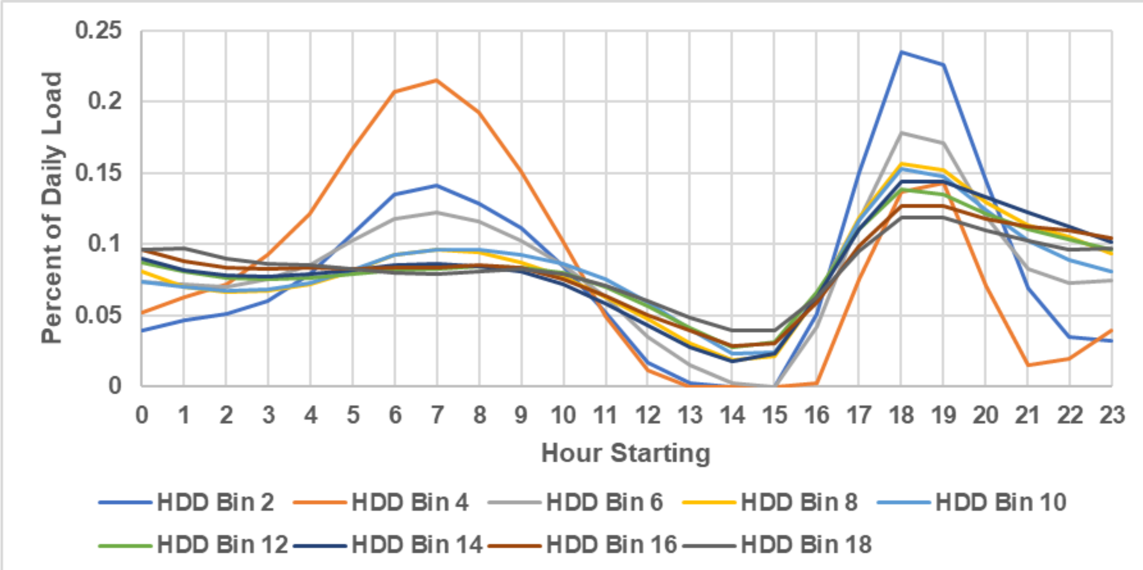
An example of cooling load shapes at different CDD bins.

Source: ADM Associates, Inc.

Heating

The approach to generating the heating load shape was described in the previous sub-section. An example of the heating load shapes is presented in Figure 140.

Figure 140: Example of Heating Load Shapes



An example of Heating load shapes at different HDD bins.

Source: ADM Associates, Inc.

Furnace Fan

Furnace fans in the residential sector typically only operate when heating or cooling is operating. Therefore, the team assumed furnace fans to be on whenever heating or cooling were on. To generate the load shape, the load shapes for heating and cooling are normalized to one for a given year to weight the two profiles equally and then aggregated together and normalized to one once more, thereby creating a normalized furnace fan load shape. An independent furnace fan load shape was not stored as the process of generating this load shape is dependent exclusively on the distribution of heating and cooling in the modeled year.

Residual Load Shape

The load shapes developed for the residential sector can be described as either analytically obtained (HVAC load shapes) or obtained from the best currently available resources (non-HVAC load shapes). Although, on an individual basis, each end-use is relatively accurate in nature, there is still potential for variation between the modeled end-uses and the aggregated data. Because the data represents an aggregate of all homes belonging to a certain building-type/forecast zone, it is not readily apparent which specific end-use causes the whole building load to deviate. It is more likely that the deviation stems from an aggregation of minor differences between the modeled end-uses and real-world factors.

Therefore, ADM developed a residual load shape. The residual load shape attempts to recover the component of the residual that is systematic and predictable and acts as a correction factor that attempts to bridge the gap between the modeled whole building load and the actual whole building load by providing a relative to correction to the modeled whole building. Unlike other load shapes, which are normalized to a total value of one per end-use, the residual load shape is normalized as a percent correction by diving each observation by the GWh for the base year for the given building-type and forecast zone of interest. It can therefore be reconstituted as a function of the relative intensity of the predicted year by multiplying the normalized profile by the modeled year's total GWh.

ADM generated the residual load shape by taking the actual residuals (difference between the actual AMI data and the modeled loads at each hour) and creating a series of coefficients segmented by time-of-year (month, day-type, and hour) and regressed against CDD and HDD. The selection of a CDD and HDD base is detailed on page 99. To accomplish this, ADM first segmented the 8,760 data by PST or PDT period, day-type (the 7 weekday-types plus an additional day-type for holidays), and hour. This resulted in 384 segments of data.

ADM then ran each segment of data through the following regression model:

$$y = \beta_0 + \beta_1 \cdot CDD + \beta_2 \cdot HDD + \varepsilon$$

Where:

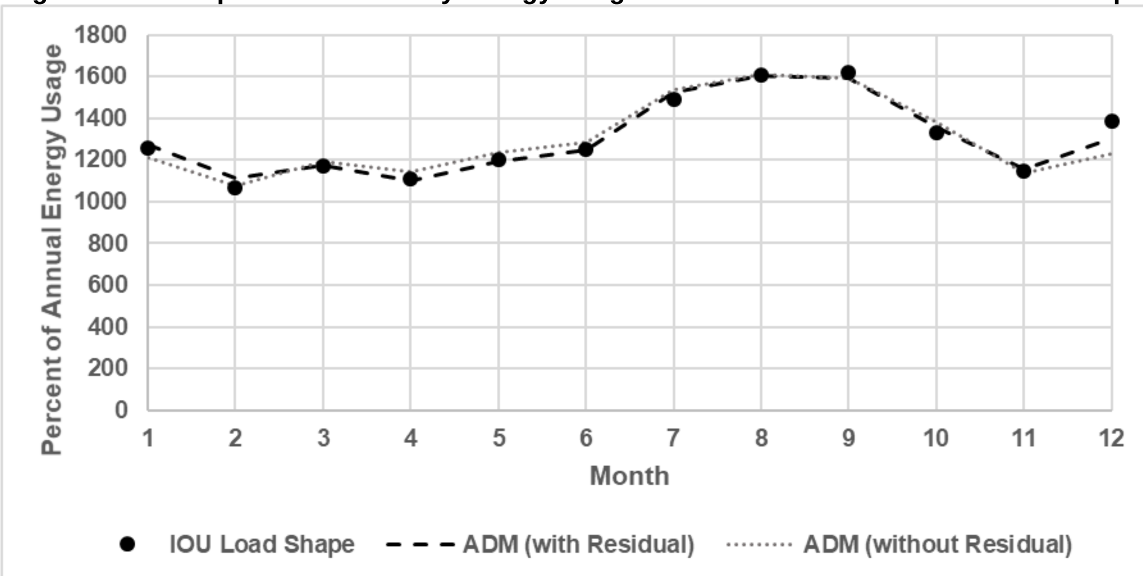
- y is the predicted normalized residual,
- β_0 is the intercept,
- β_1 is the CDD weight,
- β_2 is the HDD weight,
- And ε is the error term.

By modeling the residual this, ADM have essentially captured the variability remaining that is explainable due to temporal components and weather. Whatever residuals are remaining are therefore discarded as random.

Figure 141 through

Figure 149 provide a comparison of the whole building load shapes with and without application of the residual load shape.

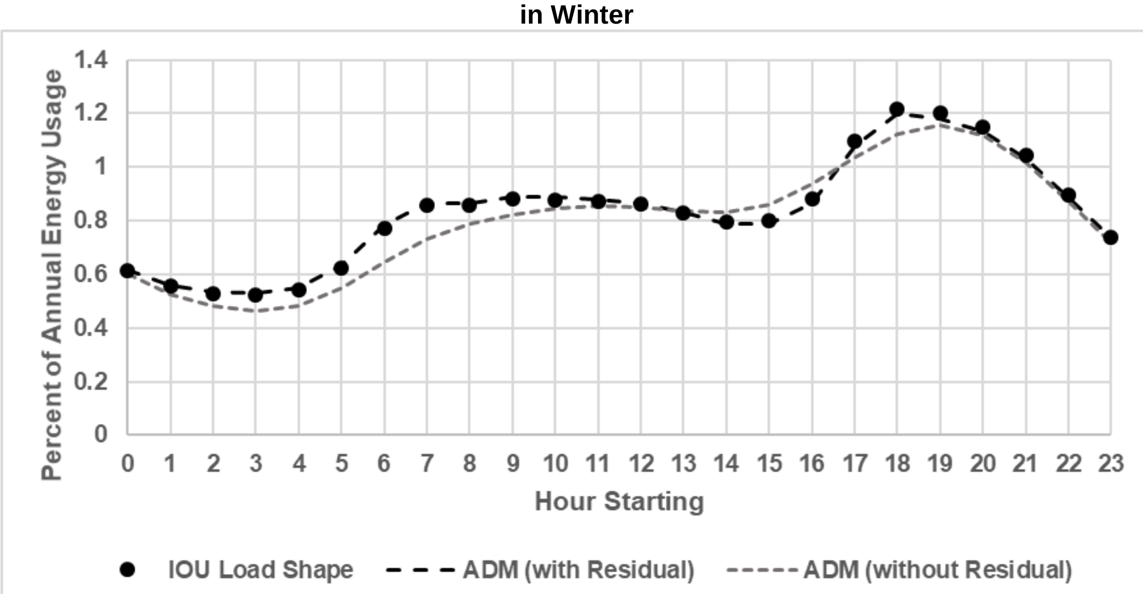
Figure 141: Comparison of Monthly Energy Usage With and Without Residual Load Shape



A comparison of the monthly energy usage at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

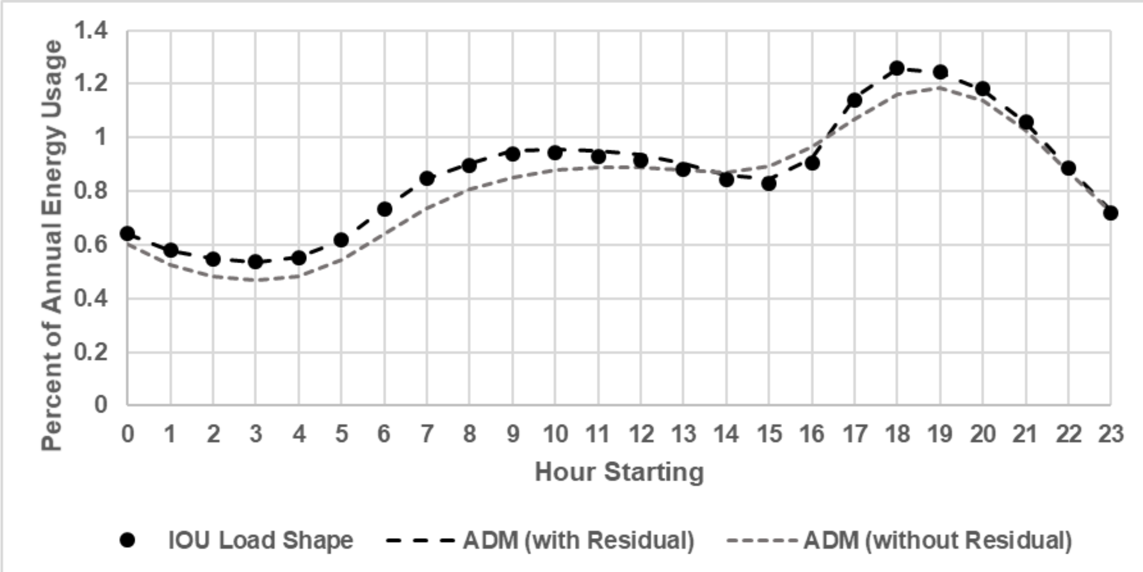
Figure 142: Comparison of the Average Daily Weekday Profile With and Without Residual in Winter



A comparison of the average daily load shape in weekdays in winter at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

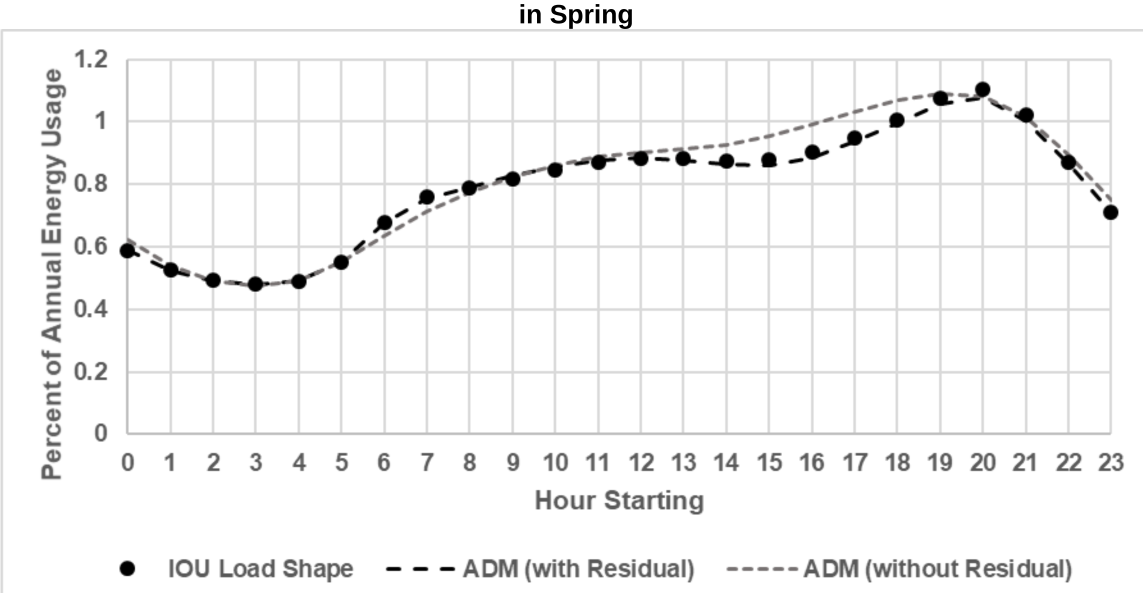
Figure 143: Comparison of the Average Daily Weekend Profile With and Without Residual in Winter



A comparison of the average daily load shape in weekends in winter at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

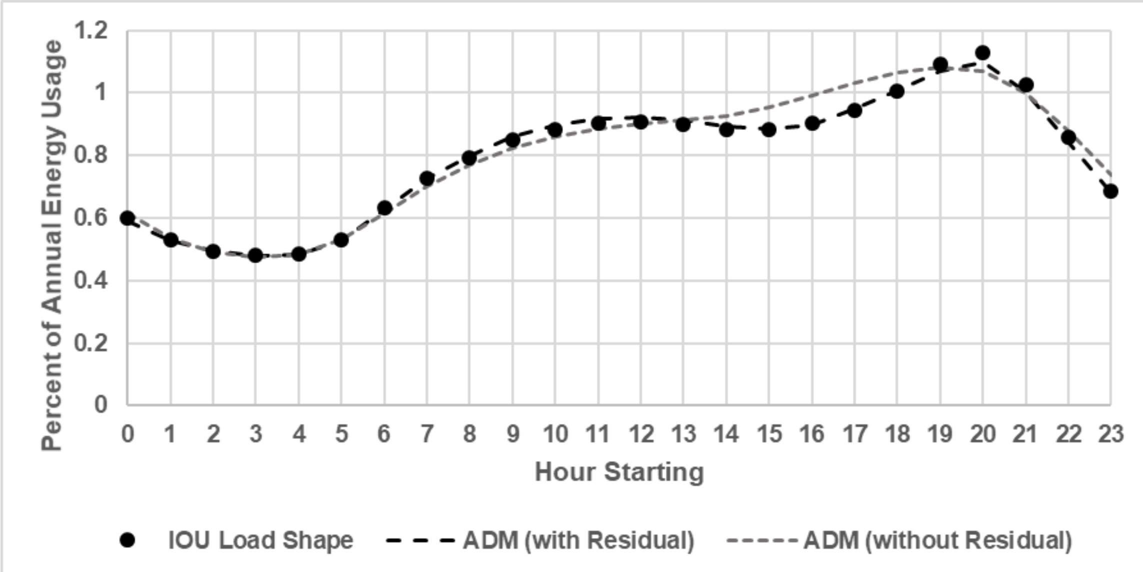
Figure 144: Comparison of the Average Daily Weekday Profile With and Without Residual in Spring



A comparison of the average daily load shape in weekdays in spring at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

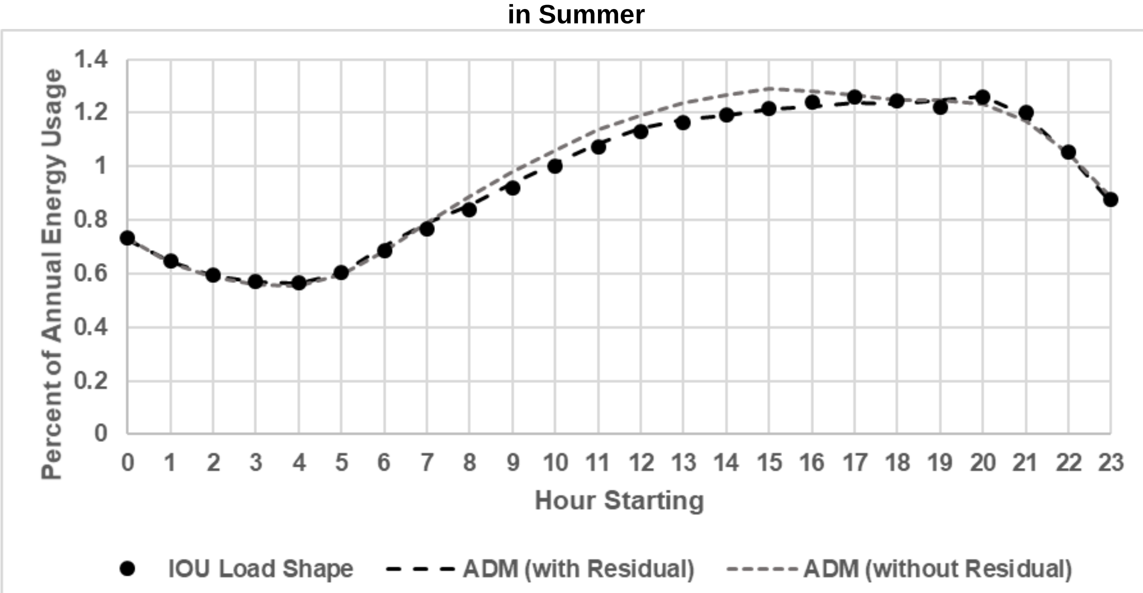
Figure 145: Comparison of the Average Daily Weekend Profile With and Without Residual in Spring



A comparison of the average daily load shape in weekends in spring at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

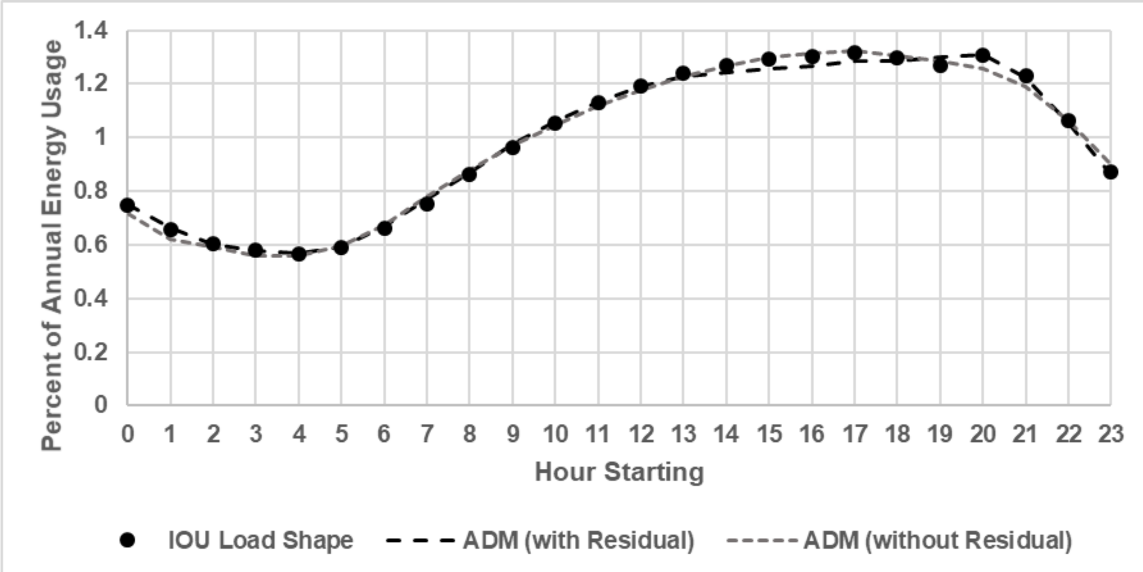
Figure 146: Comparison of the Average Daily Weekday Profile With and Without Residual in Summer



A comparison of the average daily load shape in weekdays in summer at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

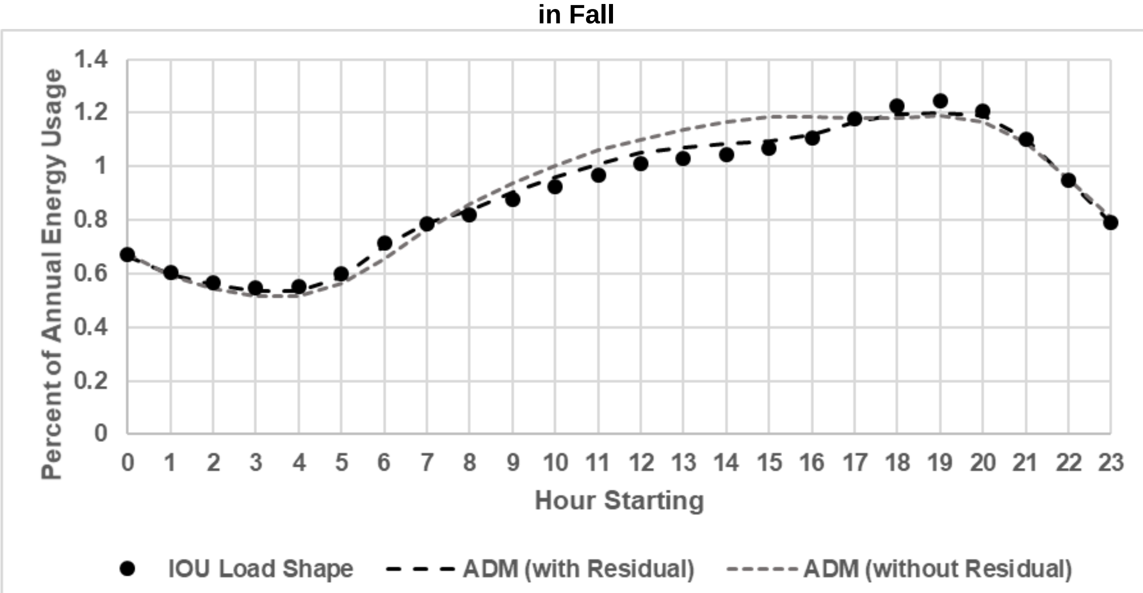
Figure 147: Comparison of the Average Daily Weekend Profile With and Without Residual in Summer



A comparison of the average daily load shape in weekends in summer at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

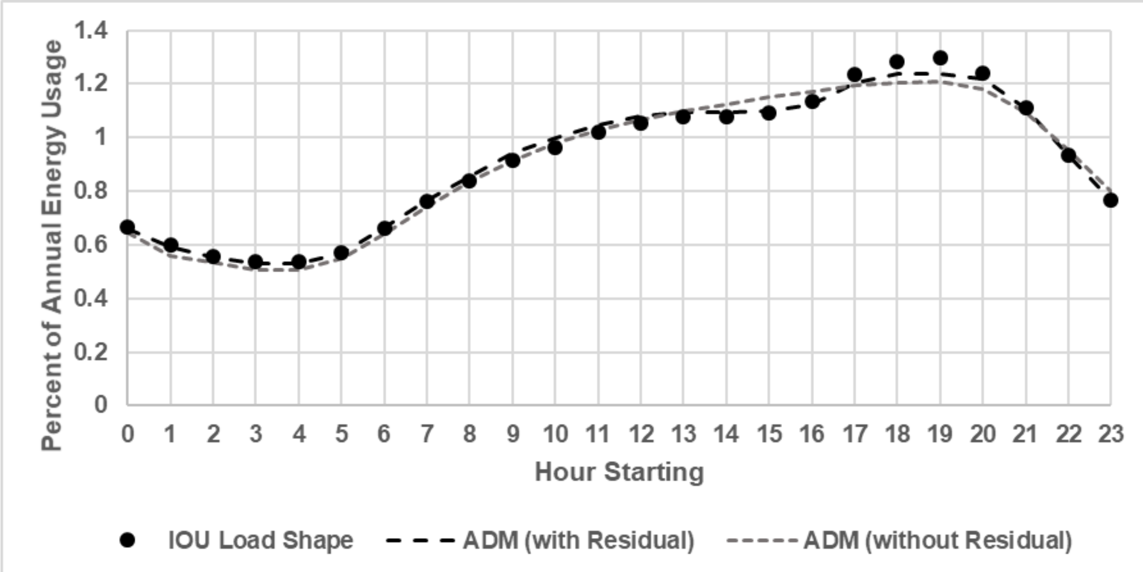
Figure 148: Comparison of the Average Daily Weekday Profile With and Without Residual in Fall



A comparison of the average daily load shape in weekdays in fall at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

Figure 149: Comparison of the Average Daily Weekend Profile With and Without Residual in Fall



A comparison of the average daily load shape in weekends in fall at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

CHAPTER 3: Base Load Shapes: Commercial Sector

Method and Data Sources

Method

Unlike the residential sector, which relied exclusively on a purely analytical method to develop the load shapes, the commercial sector relies on a hybrid model which synthesizes an analytical approach with an engineering approach. ADM relied primarily on an analytical model to create the non-HVAC loads, however, because HVAC loads in the commercial sector can often operate on an overlapping basis (i.e., heating and cooling can often be operating in one facility at the same time), ADM relied on EnergyPlus simulation models to generate the HVAC load shapes. This sub-section provides a high-level summary of the approach to the commercial sector load shapes. A detailed description of each step of the process is provided in further detail in later sections of this chapter.

The Energy Commission currently divides the Commercial sector into 12 different building-types. These 12 building-types can often include buildings that are qualitatively different from one another within the same building-type. An example of this would be the Restaurant building-type. Per the NAICS assignments used to determine the Restaurant category, Restaurants can include traditional sit-down restaurants, bars, and fast-food. These three building sub-types vary significantly in their operating schedule. Therefore, the aggregation of these three building sub-types can lead to internal load shapes that are difficult to craft engineering models for. Prior to requesting AMI data from the three California IOUs, ADM divided the 12 building-types into 27 building sub-types, with the intention of modeling non-HVAC loads on the 12 building-types and modeling HVAC loads first on the 27 building sub-types prior to aggregating the load shapes back to the 12 building types. Table 2 presents the 12 building-types and corresponding building sub-types.

Table 2: Commercial Building-Types

Building-Type	Building Sub-Type
College	Academic Education
College	Non-instructional educational services
College	Specialized/Other Education
Food	Convenience
Food	Grocer
Food	Specialty Food
Health Care	Hospitals
Health Care	Nursing and Assisted Living
Health Care	Outpatient health care
Hotel	Casinos
Hotel	Hotels and Motels
Hotel	Other lodging
Misc	Data Center Like
Misc	Education-Like
Misc	Office-Like
Misc	Other Misc
Misc	Retail-Like
Office (Small/Large)	Office
Refrigerated Warehouse	Refrigerated Warehouse
Restaurant	Bar
Restaurant	Fast Food
Restaurant	Other Restaurant
Restaurant	Sit-Down
Retail	Retail
School	Educational Services
School	School
Warehouse	Warehouse

Presentation of the 12 building-types and corresponding building sub-types.

Source: ADM Associates, Inc.

ADM first began by sourcing new internal load shapes for non-HVAC load shapes. The team used load shapes derived from the CEUS (Itron, Inc. 2006) the basis for the internal load shapes. However, ADM anticipated that load shapes have shifted from the last CEUS. In general, ADM expects that shifts in working hours and changes in equipment efficiency will have shifted load shapes from being peaked to more distributed. Therefore, the researchers created an analytical approach to modify the load shapes relative to the averaged building-type AMI data the researchers received from the IOUs. ADM performed this approach once on data corresponding to the 12 building sub-types for use in the final base year load shapes and once on data corresponding to the 27 building sub-types for use as a basis for the engineering model internal load schedules.

After generating internal load schedules for each building sub-type, the schedules are then used as the basis for the internal load schedules for the EnergyPlus simulation models. The purpose of modifying the internal load schedules this way is to ensure that any HVAC interactions are modeled appropriately, as opposed to using the prototypical load shapes pre-constructed in each building model. EnergyPlus simulation models are designed to generate outputs for single buildings. Because the goal is to create load shapes that represent a group of buildings, the output for a single EnergyPlus simulation model will fail to capture the true variability of the sector. Therefore, for each of the 27 building sub-types per forecast zone, the ADM then ran a set of EnergyPlus simulation models, varying the HVAC setpoint schedules.

Once the EnergyPlus simulation models have been created, ADM then use the building sub-type AMI data to create a fixed regression to determine the appropriate weight of each simulation in generating average HVAC load shapes. ADM then aggregates those HVAC load shapes back to the 12 building-types per forecast zone based on the relative contribution of each building sub-type to its corresponding building-type. At this point, all end-use load shapes are compressed to a series of regression coefficients per building-type per forecast zone. For non-HVAC coefficients, the load shapes are compressed to 24-hour x day-type x month matrices. For HVAC coefficients, the load shapes are compressed by either CDH or HDH x day-type x month.

After compressing the load shapes to a series of regression coefficients, ADM used the coefficients to regenerate the load shapes for the three base years (2014-2016) and generated the residual for each hour. This residual is then modeled using a CDH, HDH, day-type, and month regression model to capture the systematic component of the residual. Pieces of this newly constructed residual load shape are then used to scale the regression coefficients for the end-use load shapes on a monthly or month x day-type level. After adjusting the end-use load shape coefficients, a final residual load shape is then generated.

Data Sources

The following section provides a list of the data sources used to generate the load shapes. In addition to listing the data source, a brief description of the data source and any data preparation activities are provided.

AMI Data

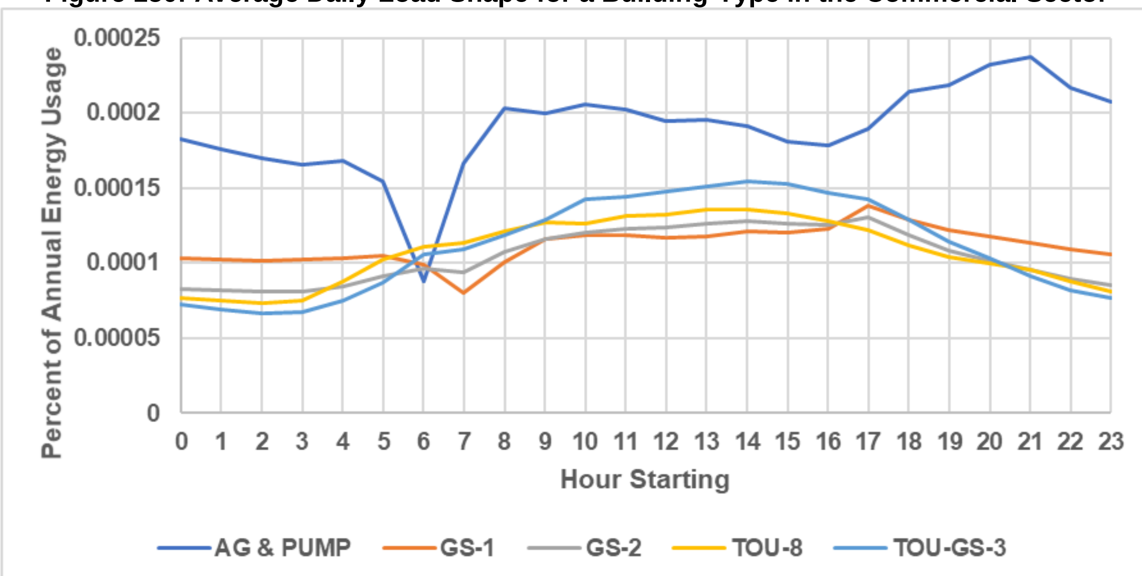
As part of this project, a data request was submitted to the three California IOUs requesting data for all non-residential sectors from the years 2014, 2015, and 2016. In response to this data request, the three IOUs provided averaged hourly data by building sub-type and either usage level (PG&E and SDG&E segmented data by high, medium, and low users) or rate class (SCE).

Prior to using the interval meter data, ADM first pre-treated all data. This pre-treatment consisted of standardizing the nomenclature of all files and merging the dataset with climate-zone specific hourly historical weather data obtained from the Energy

Commission. Hourly timestamps were standardized to units of PST for the entire year (11 p.m. PDT was standardized to 10 p.m. PST). Data was restricted to January 1, 2014 through December 31, 2016.

As part of the data validation process, the researchers reviewed the data provided by the IOUs. ADM data for gaps and significant spikes within the data over the year. In some cases, ADM noticed jagged-ness, atypical gaps, or convergence of different rate class profiles. An example of an average daily profile for each rate-class for a building-type in a single forecast zone is presented in Figure 150.

Figure 150: Average Daily Load Shape for a Building-Type in the Commercial Sector



An example of the average daily profile for all rate classes belonging to a single building-type in a single forecast zone in the commercial sector.

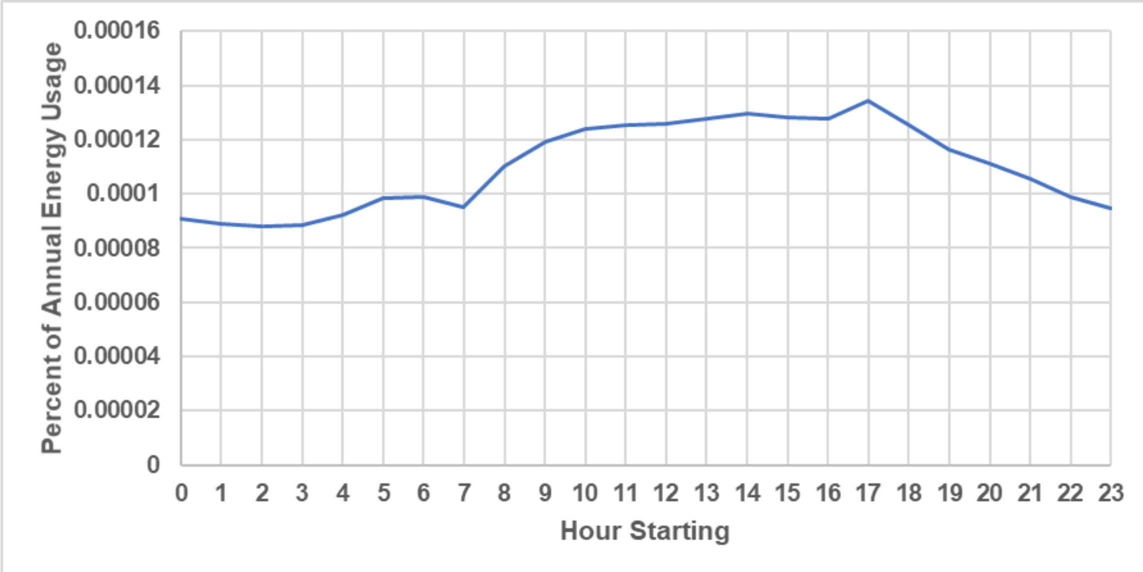
Source: ADM Associates, Inc.

As seen in the plot, the load shapes for one of the general services rate classes (GS-2), and two of the time-of-use rates (TOU-8 and TOU-GS-3) bear a strong resemblance to one another. However, the profiles for agriculture and pumping (AG & PUMP) and one of the general services rates (GS-1) show atypical patterning in that both have unexpected drops at specific hours. Furthermore, the intensity of the AG & PUMP shape is significantly higher than the other load shapes (and, consequently, lower in other months). The underlying cause of these patterns can be attributed to multiple causes, such as changing of rate class for some meters over the year, or misattribution of sub-meters to a specific rate class.

Because ADM cannot assume that these types of anomalies are attributable to data artifacts, ADM blended the profiles for each building sub-type across rate class. The result of blending the rate class level load data from Figure 150 as shown in

Figure 151.

Figure 151: Average Daily Load Shape for a Building-Type in the Commercial Sector Post-Aggregation



An example of the average daily profile after aggregating across rate classes for a single building-type in a single forecast zone in the commercial sector.

Source: ADM Associates, Inc.

As can be seen, aggregating the different rate classes together generates a load shape that reduces the anomalies attributable to any given rate class load shape. Although the example shown illustrates this process for data sets segmented by rate class, these patterns also exist in the data sets that were segmented by usage level. Therefore, all data segments per building sub-type per forecast zone were aggregated together.

Commercial Building Energy Demand Forecast Model

The Commercial Building Energy Demand Forecast Model is the component of the CED Model that predicts the overall annual energy usage for a given end-use at the forecast zone level. The predicted GWh is further subdivided by building type. For example, the model has predictions of the total annual interior lighting GWh for all colleges in forecast zone 1. Updates are made to the model on an annual basis, with major revisions occurring bi-annually. The Energy Commission corrects its historical load forecast based on observed whole-building energy use on an annual basis, thereby adjusting the end-use level forecast based on the total observed load.

As part of the process of developing load shapes for the base years of 2014, 2015 and 2016, ADM leveraged the weather-adjusted forecast values from the Commercial Building Energy Demand Forecast Model for 2014, 2015 and 2016 and assumed that the overall energy usage per end-use was distributed in the same proportions as the model.

Weather Data

An extract of weather data was supplied by the Energy Commission for 2014-2016. Weather data consisted of outdoor air temperature, dew point, precipitation, windspeed, wind direction, total sky cover, and mean sea level pressure. Weather files were generated for all major AWS in California. The Energy Commission provided weighting files meant to define the appropriate weighting of each AWS to generate a forecast-zone-level weather file.

California Commercial End-Use Survey

The most recent CEUS was published in 2006 by Itron, Inc. and provides information regarding the total floor stock, energy intensity, and percent energy distribution for 13 different end-uses. Additionally, the 2006 CEUS provides 8,760 load shapes per end-use. The end-uses captured in the 2006 CEUS were:

- Air compressor
- Cooking
- Cooling
- Exterior lighting
- Heating
- Interior lighting
- Miscellaneous
- Motors
- Office equipment
- Process
- Refrigeration
- Ventilation
- Water heating

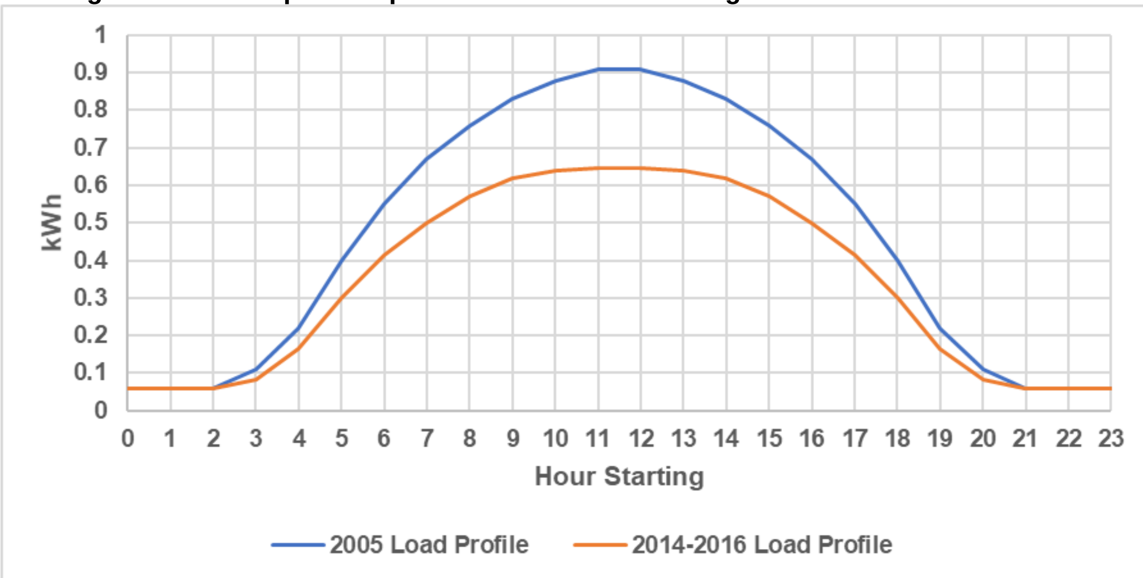
Results were presented by building type, forecast zone, and utility company. Forecast zones use a stale-dated scheme of ten forecast zones for the three IOUs. The Energy Commission currently uses a 12-forecast zone schematic, therefore, the ADM reviewed data at a building type by utility company level.

Pre-Simulation Modeling

Although ADM has sourced new end-use load shapes from the CEUS (Itron, Inc. 2006), there may still be differences in the load shapes in the current base period of 2014-2016 compared to the 2005 base year used by the CEUS.

Figure 152 provides a hypothetical example of an average daily profile in 2005 compared to an average daily profile in 2014-2016.

Figure 152: Example Comparison of a Whole Building Load in 2005 vs. 2015-2016



Hypothetical comparison of a daily load shape in a building in 2005 compared to a building in 2014-2016.

Source: ADM Associates, Inc.

In general, one can anticipate that the energy use in 2014-2016 has reduced, on average, due to changes in building code and improved energy efficiency. In addition, the peak of the curve is not as pronounced in 2014-2016 relative to 2005. This assumption can be made because the energy efficiency improvements between 2005 and 2014-2016 are likely to be lighting and office equipment-based improvements, which will reduce the relative impact of lighting compared to the other end-use loads and consequently minimize interactive effects in HVAC loads.

Additionally, the load shapes from CEUS, as well as the GWhs predicted by the Commercial Building Energy Demand Forecast Model, are generated at a higher level than the building types used by ADM. For example, restaurants have been broken down into several sub-types for the purpose of this study. Therefore, ADM needed to adapt the load shapes from the 2006 CEUS to match changes in 2014-2016 due to shifts in energy efficiency and match the load shapes to the building sub-type from the original building type.

To adapt the load shapes, ADM used the following approach:

1. For a given building sub-type in a given forecast zone, project analysts selected the corresponding major building-type end-use load shapes for the same IOU from the 2006 CEUS—because forecast zones were redesigned between the time of the last CEUS and present day, were not able map the load shapes at a more granular, forecast zone resolution.
2. Outdoor lighting load shapes were developed independently based on historical sunrise/sunset data. Outdoor lighting was then subtracted from the IOU data

based on its relative weight as predicted from the Commercial Building Energy Demand Forecast Model.

3. After selecting the appropriate load shape, ADM used the annual demand per end-use for the major building type for that specific forecast zone as predicted by the Commercial Building Energy Demand Forecast Model to estimate the relative weight of each end-use load shape for that building type and forecast zone. The load shapes were then scaled appropriately. Non-HVAC loads were then aggregated to generate an estimate of the 2014 whole-building load shape in absentia of HVAC related loads.
4. The IOU load shape for 2014 and the CEUS-based load shape were normalized, and February was isolated as the "base month." This is because February showed the least amount of weather-dependence upon exploratory analysis, suggesting a limited impact of HVAC in this month.
5. After isolating February for the IOU load shape and the CEUS-based load shape, the project team ran an hour-matching algorithm. This hour-matching algorithm looked at every hour in the IOU load shape relative to its percent of peak in that same day and found its closest match in the corresponding weekday types in the CEUS data. For example, for 1 a.m. Monday, February 3, 2014, the algorithm looked at all Mondays in the CEUS load shape and found the hour it most closely resembled across all Mondays of the CEUS load shape.

6. Table 3 provides an example of ADM's hour-matching algorithm for a sample 24-hour period.

Table 3: Example of Hour-Matching the 2014-2016 Profile to the 2005 Profile

Hour	Load shape in 2014-2016	Load shape in 2005	Matched Hour
0	0.007057678	0.005268895	0
1	0.007057678	0.005268895	1
2	0.007057678	0.005268895	2
3	0.010038939	0.009992733	3
4	0.020077878	0.019985465	4
5	0.036505232	0.036337209	5
6	0.050194695	0.049963663	6
7	0.060842054	0.060864826	7
8	0.069359942	0.069040698	8
9	0.075444147	0.075399709	9
10	0.077877829	0.07994186	10
11	0.07848625	0.082667151	10
12	0.07848625	0.082667151	10
13	0.077877829	0.07994186	10
14	0.075444147	0.075399709	14
15	0.069359942	0.069040698	15
16	0.060842054	0.060864826	16
17	0.050194695	0.049963663	17
18	0.036505232	0.036337209	18
19	0.020077878	0.019985465	19
20	0.010038939	0.009992733	20
21	0.007057678	0.005268895	21
22	0.007057678	0.005268895	22
23	0.007057678	0.005268895	23

Hypothetical example of hour-matching of a daily load shape in the 2015-2016 base year to the 2005 whole building load shape.

Source: ADM Associates, Inc.

7. After finding the matched-hour for each hour of the IOU profile, the IOU profile is then disaggregated based on the percent-of-each-end-use present for the matched-hour in the scaled CEUS profile.
8. The February end-use profiles are then extrapolated back to an 8,760-load shape. For the five education-related load shapes, a scaler is applied prior to extrapolating to an 8,760-load shape. Based on the original IOU data, a scaler is generated for the average daily energy use in September divided by the average daily energy use in August. For January through May and September through December, the profiles are scaled relative to the September to August scalar.

As noted previously, the pre-simulation modeling occurs once at the 12 building-type resolution and once again at the 27 building-type resolution. This is done to reduce the number of manipulations are necessary to generate the final load shapes. ADM's goal is to ultimately generate load shapes for the 12 building-types that are used by the Energy Commission in the CED Model. By segmenting the profile into its 27 building sub-types, using those profiles in the EnergyPlus models, and then aggregating the end-use profiles to their original 12 building-types, one introduces multiple points at which the profiles may change or shift due to data restructuring or manipulation. By running the process twice, ADM can ensure that appropriate schedules feed into the EnergyPlus models while still retaining unaltered profiles for the 12 building-types.

Parametric EnergyPlus Models

To capture the interactive effects of HVAC loads in the commercial sector, ADM used EnergyPlus simulations to generate HVAC load shapes (Table 4). The EnergyPlus models were sourced from The U.S. Department of Energy (DOE) Commercial Prototype Building Models (Pacific Northwest National Laboratory 2018). The prototype models include 12 commercial building types which were used to develop the 27 building sub-types per forecast zone. ADM's calibration process involved modeling various circumstances that encompass most scenarios, where each scenario differed by the selected variable's magnitudes. The magnitude of specific variables was modified via parametric processing where the framework of the model could remain static. This allowed ADM to see the effects of modifying each specific variable. Using the parametric functionality also allowed the ADM to scale up the total number of models and variables which increased dramatically when simulating 27 building sub-types in each weather forecasting zone with several parametric variables each.

Table 4: Example Parametric Combination Matrix

<table>
<tr><th colspan="2" rowspan="2">Magnitude Interactions</th><th colspan="3">Variable #1</th></tr>
<tr><th>High</th><th>Medium</th><th>Low</th></tr>
<tr><th rowspan="3">Variable #2</th><th>High</th><td>Run #1</td><td>Run #2</td><td>Run #3</td></tr>
<tr><th>Medium</th><td>Run #4</td><td>Run #5</td><td>Run #6</td></tr>
<tr><th>Low</th><td>Run #7</td><td>Run #8</td><td>Run #9</td></tr>
</table>

Example of how parametric combinations result in different EnergyPlus runs used by ADM in load shape development.

Source: ADM Associates, Inc.

Parametric functionality in EnergyPlus allowed ADM to efficiently and reliably create and simulate numerous results, but the dramatic increase in results compared to variables resulted in the need for batch runs using R.

Batch Runs Through R/EnergyPlus Integration

The programming language R is used to control EnergyPlus. Although R is usually used for data handling and statistical modeling, it is also suitable as a scripting language for developing input files and automating many tasks which could not be done manually at this scale. One of the reasons EnergyPlus was selected as the simulation tool is because it can be run from the command line as an executable, and the input files can be modified extensively without intermediate software. This flexibility enabled ADM to scale building simulation to the thousands of runs required to generate load shapes at this level of detail.

Approximately 40 R scripts were written to complete the operations needed to run EnergyPlus to develop load shapes. Some of the major operations included:

- Create EnergyPlus weather file
- Update input files to use end-use coefficients from the pre-simulation model
- Generate setpoint schedules for the HVAC subsystems
- Run EnergyPlus Parametric pre-processor to develop individual runs with various physical parameters and schedules
- Produce batch file by climate zone to run EnergyPlus models at scale
- Map prototypical buildings to represent building subcategories used for load shapes

These scripts were managed in a code repository and used industry standard R best practices where possible to make iterations rapid and improve code durability.

Calibration for Commercial Models

Because the AMI data provided by the IOUs is aggregated in nature, it is unlikely that any given simulation will be able to accurately represent the overarching load shape for an entire sector. This is because simulation models represent load shapes as discrete operating schedules. While this would be true of an individual building, at an aggregated level, load shapes shift from discrete to continuous in nature because some portion of the population of interest will still be contributing to that end-use load at less common times. For example, 7 a.m. on a summer day would most likely only have a small proportion of all buildings using central air conditioner. However, a simulation model may assume that the end-use is completely off during that period.

The parametric simulations encompass varying circumstances that account for most scenarios. Therefore, each simulation represents some proportion of the underlying population, although the relative weight of each simulation in its contribution to the population-level load is unknown. Instead of attempting to select a single simulation model that best encapsulates the population-level AMI data, the goal through calibration was to approximate the percent to which each simulation model contributes to the population.

To accomplish this goal, ADM relied on linear optimization via a constrained regression model. The constraints placed on the regression aim to replicate two real-world assumptions:

1. There is no "intercept" term because the aggregated AMI-load shape should be fully encompassed in the parametric simulations.
2. Although the impact of a given parametric simulation can be 0, it cannot contribute negatively to the overall load.

The regression model for the calibration is specified as follows:

$$kWh_{AMI} = \emptyset + \beta_1 \cdot EnergyPlus_1 + \cdots + \beta_n \cdot EnergyPlus_n$$

Where:

- kWh_{AMI} is the billing data load
- $\emptyset$ is a fixed intercept term of 0
- β_1 is the weight of the first EnergyPlus run
- β_n is the weight of the last EnergyPlus run

ADM anticipated that some of the parametric simulation models may overlap and be collinear to one another. In an unconstrained regression, this can result in compensatory weighting in which one independent variable may be extremely negative while another becomes extremely positive. However, by constraining the regression, one can assume that the variability associated with the two models will either distribute themselves randomly amongst the two models, or one model will be weighted as 0 while the other model retains the full weight attributable to both models. Therefore, ADM was not concerned about either phenomenon occurring as collinearity between two models suggests that either model can explain both simulation parameters sufficiently well.

After determining the relative weight of each simulation model, the load shapes for all simulation models were blended together in the relative proportion as determined by the regression coefficients.

Post Calibration Modeling

The post-calibration modeling primarily consisted of compressing the three HVAC loads (cooling, heating, and ventilation) to a series of predictive coefficients that can be used to generate these load shapes in periods outside of the 2014 base year. As noted previously, the seven non-HVAC loads were compressed at a month x hour resolution as part of the process of modifying the CEUS (Itron, Inc. 2006) load shapes into predictive load shapes for the 2014 base year for the 27 building sub-types and for the 12 building types used by the Energy Commission.

Dividing the 12 Energy Commission building types into further building sub-types facilitated EnergyPlus simulations, as the impact of efficiency measures can have significant differences on buildings that may be categorized in the same building type but are functionally different (for example, an outpatient health care facility versus a hospital). However, ADM are ultimately concerned with consolidating those impacts back into the 12 building types used by the CED Model. Therefore, after consolidating the EnergyPlus runs into a single run per building sub-type per forecast zone using the calibration weights, ADM then consolidated from the 27 building sub-types to the 12 Energy Commission building types using weighting files provided by the three IOUs as part of their fulfillment of the data request. What results are load shapes that approximate the average load shape for all buildings of a given building type in a forecast zone.

ADM first began by normalizing the heating, cooling, and ventilation load shapes to an annual sum of one per load. After normalizing the load shapes, the AD< then segmented the data by PST/PDT, day-type, and hour. Although ADM could model the three-way interaction of PST/PDT, day-type, and hour in one consolidated regression, doing so would result in the regression exceeding the bounds of normal computing resources. Segmenting the data set allows for the arrival at a mathematically identical result while conserving computing resources. CDH and HDH values were generated for each data set using the appropriate hourly weather data. Each data segment was then run through a simple weather-based linear regression.

The regression model for cooling is specified as follows:

$$y = \beta_0 + \beta_1 \cdot CDH + \varepsilon$$

Where:

- y is the modeled cooling load for a given hour
- β_0 is the intercept
- β_1 is the CDH weight
- ε is the model error

The regression model for heating is specified as follows:

$$y = \beta_0 + \beta_1 \cdot HDH + \varepsilon$$

Where:

- y is the modeled heating load for a given hour
- β_0 is the intercept
- β_1 is the HDH weight
- ε is the model error

The regression model for ventilation is specified as follows:

$$y = \beta_0 + \beta_1 \cdot CDH + \beta_2 \cdot HDH + \varepsilon$$

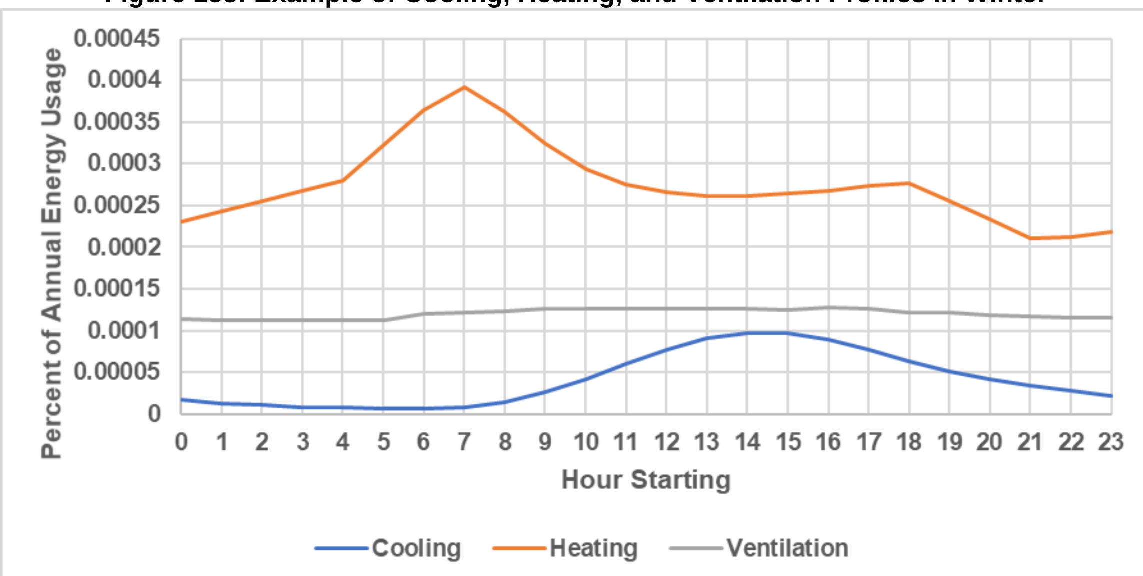
Where:

- y is the modeled ventilation load for a given hour
- β_0 is the intercept

- β_1 is the CDH weight
- β_2 is the HDH weight
- ε is the model error

After generating coefficients at a PST/PDT x day-type x hour resolution, ADM upscaled the coefficients to a 12-month x day-type x hour resolution. This allowed ADM to further manipulate the load shapes for colleges and schools (described in a later section), as there is a significant interaction between the HVAC load and month. Examples of the heating, cooling, and ventilation loads for a commercial building are provided in Figures 153-156.

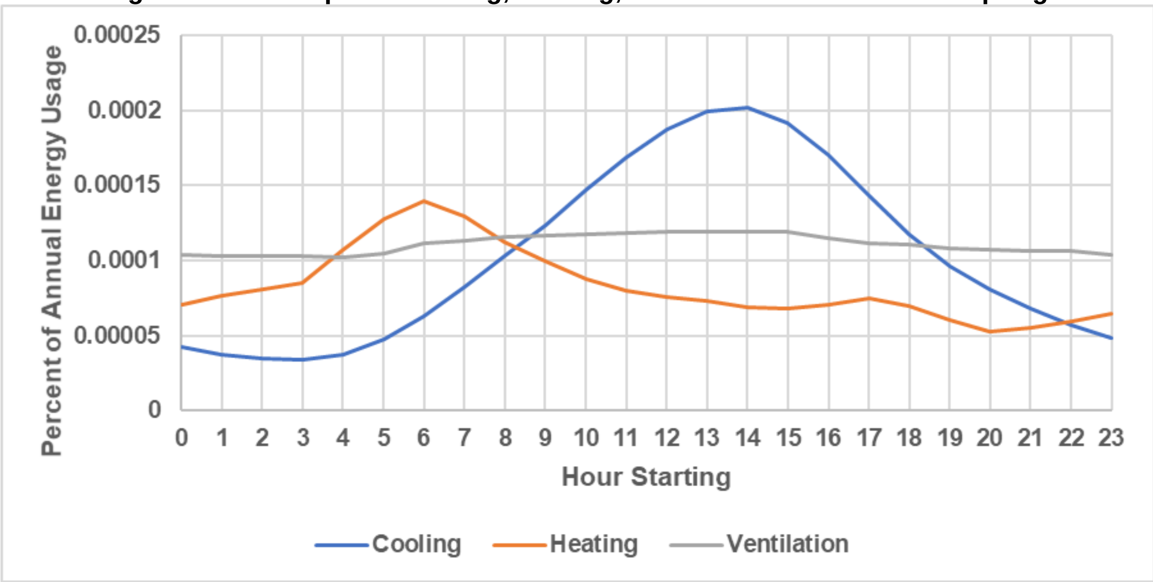
Figure 153: Example of Cooling, Heating, and Ventilation Profiles in Winter



Example of the average weekday daily load shape for cooling, heating, and ventilation in the months of December, January, and February for a building type in a given forecast zone.

Source: ADM Associates, Inc.

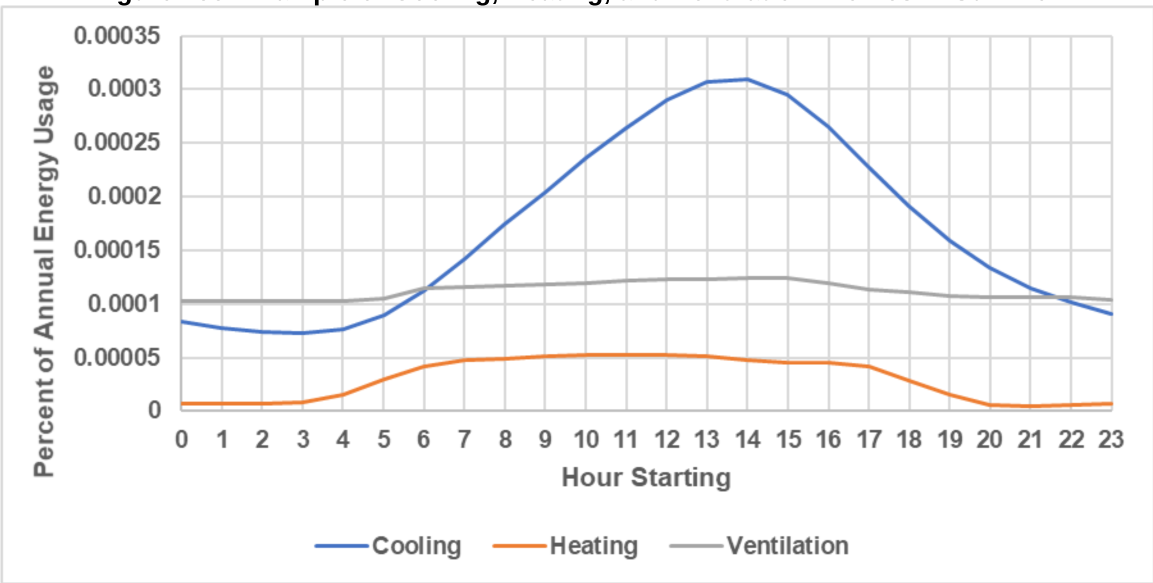
Figure 154: Example of Cooling, Heating, and Ventilation Profiles in Spring



Example of the average weekday daily load shape for cooling, heating, and ventilation in the months of December, January, and February for a building type in a given forecast zone.

Source: ADM Associates, Inc.

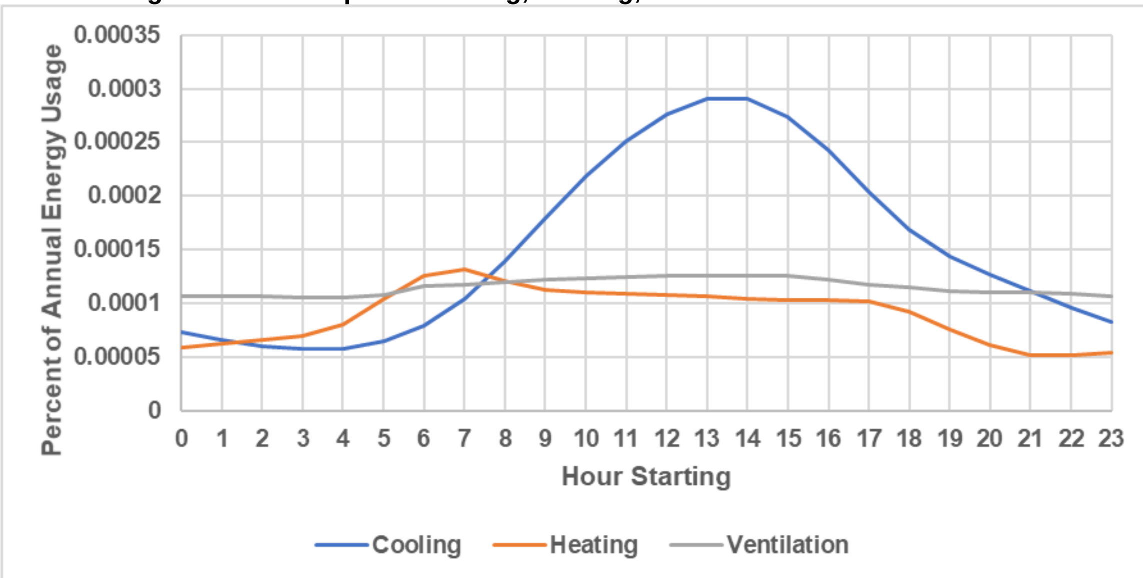
Figure 155: Example of Cooling, Heating, and Ventilation Profiles in Summer



Example of the average weekday daily load shape for cooling, heating, and ventilation in the months of December, January, and February for a building type in a given forecast zone.

Source: ADM Associates, Inc.

Figure 156: Example of Cooling, Heating, and Ventilation Profiles in Fall



Example of the average weekday daily load shape for cooling, heating, and ventilation in the months of December, January, and February for a building type in a given forecast zone.

Source: ADM Associates, Inc.

Because ADM is deriving cooling and heating profiles from EnergyPlus simulation data, the temperature at which cooling or heating "turns on" is a known value. This value, however, could vary from run-to-run and from building sub-type to building sub-type and may not be accurately reflected in the consolidated profiles. Therefore, ADM used the outside air temperature at which either cooling or heating load rose above 0 as the starting point for finding a CDH or HDH base. For cooling, ADM tested all potential CDH bases between the starting point and 80 degrees Fahrenheit. For heating, ADM tested all potential HDH bases between 50 degrees Fahrenheit and the ending point. ADM used the lowest normalized root mean square error (NRMSE) of each potential base for modeling the load shapes to determine the optimal CDH or HDH base. NRMSE provides a normalized measurement of the deviation of predicted values of a model from observed values and can be calculated as:

$$NRMSE = \sqrt{{(\sum_i^n (x_i - y_i)^2)}/{n}} \Big/ \bar{x}$$

Where:

- x is the observed building kW for the data set of interest,
- y is the predicted building kW from the regression model,
- i represents each instance in the data set,
- and n represents the total number of observations in the data set.

CDH and HDH bases were then stored in a table for later use.

Residual Load Shape

Although the parametric simulations encompass most scenarios underlying the aggregated AMI data provided by the IOUs, there is still potential for variation between the final, calibrated models and the aggregated AMI data. Because the data represents an aggregate of all buildings belonging to a certain building-type/forecast zone, it is not readily apparent which specific end-use causes the simulation model to deviate. It is more likely that the deviation stems from an aggregation of minor differences between the modeled load shapes and real-world factors.

Therefore, ADM developed a residual load shape. The residual load shape attempts to recover the component of the residual that is systematic and predictable and acts as a correction factor that attempts to bridge the gap between the modeled whole building load and the actual whole building load by providing a relative to correction to the modeled whole building. Unlike other load shapes, which are normalized to a total value of one per end-use, the residual load shape is normalized as a percent correction by diving each observation by the GWh for the base year for the given building-type and forecast zone of interest. It can therefore be reconstituted as a function of the relative intensity of the predicted year by multiplying the normalized profile by the modeled year's total GWh.

ADM generated the residual load shape by taking the actual residuals (difference between the actual AMI data and the modeled loads at each hour) and creating a series of coefficients segmented by time-of-year (month, day-type, and hour) and regressed against CDH and HDH.[4]. To accomplish this, ADM first segmented the 8,760 data by month, day-type (the seven weekday-types plus an additional day-type for holidays), and hour.

ADM then ran each segment of data through the following regression model:

$$y = \beta_0 + \beta_1 \cdot CDH + \beta_2 \cdot HDH + \varepsilon$$

Where:

- y is the predicted normalized residual
- β_0 is the intercept
- β_1 is the CDH weight
- β_2 is the HDH weight
- ε is the model error

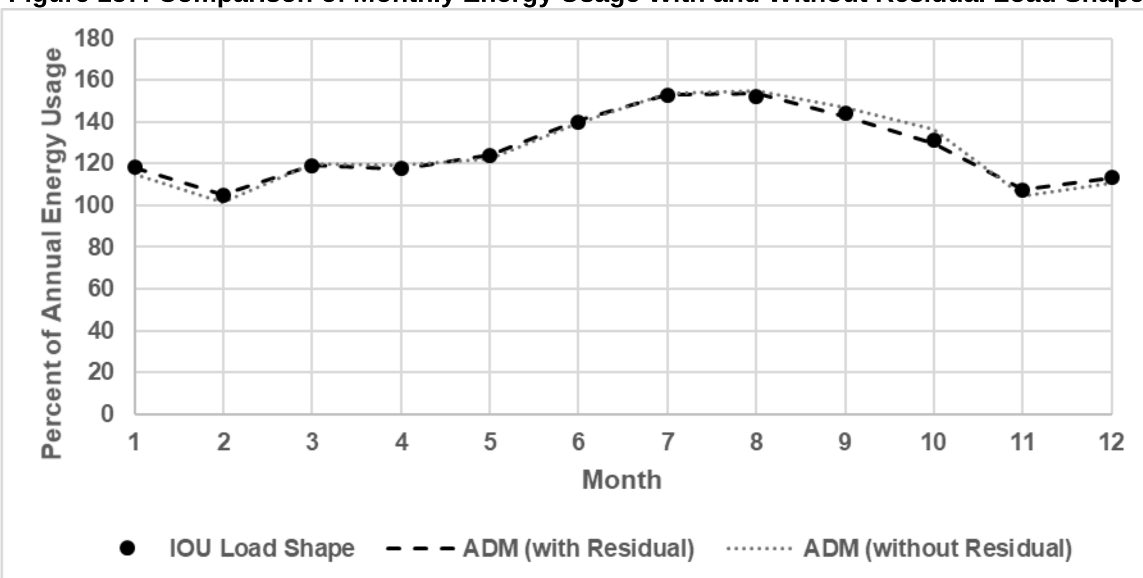
4 The selection of a CDD and HDD base is detailed in the "Post Calibration Modeling" section beginning on page 118

By modeling the residual this, ADM has essentially captured the variability remaining that is explainable due to temporal components and weather. Whatever residuals are remaining are therefore discarded as random.

Figure 157 through

Figure 165 provide a comparison of the whole building load shapes with and without application of the residual load shape.

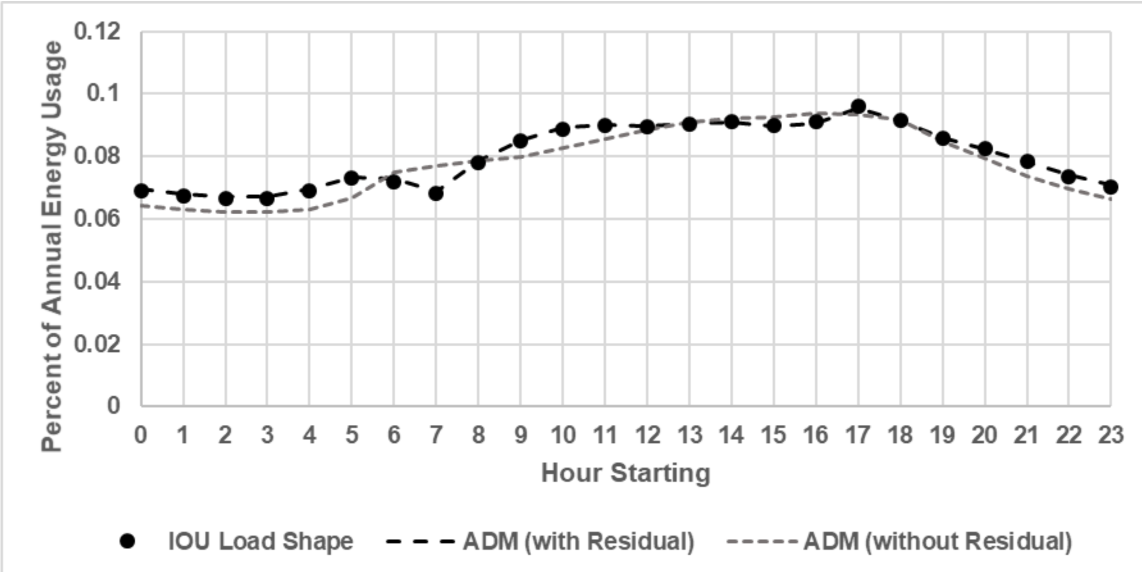
Figure 157: Comparison of Monthly Energy Usage With and Without Residual Load Shape



A comparison of the monthly energy usage at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

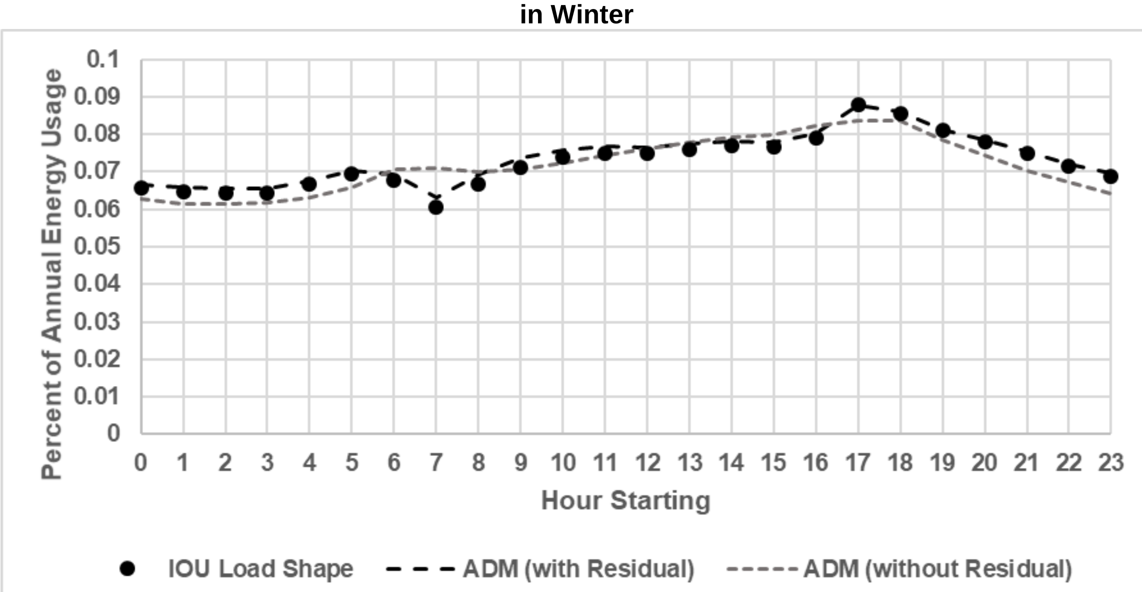
Figure 158: Comparison of the Average Daily Weekday Profile With and Without Residual in Winter



A comparison of the average daily load shape in weekdays in winter at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

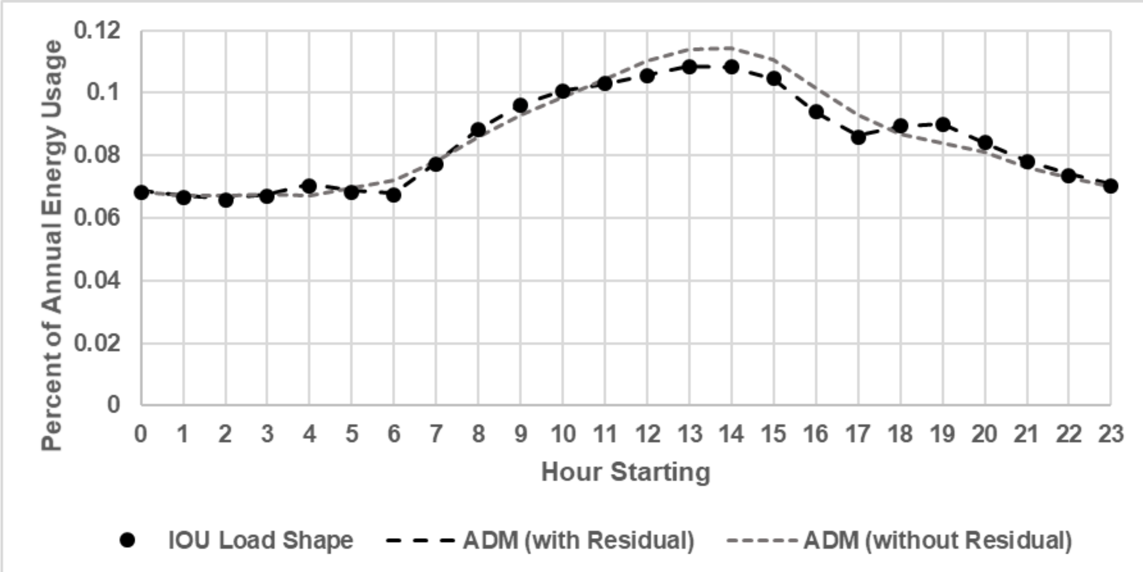
Figure 159: Comparison of the Average Daily Weekend Profile With and Without Residual in Winter



A comparison of the average daily load shape in weekends in winter at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

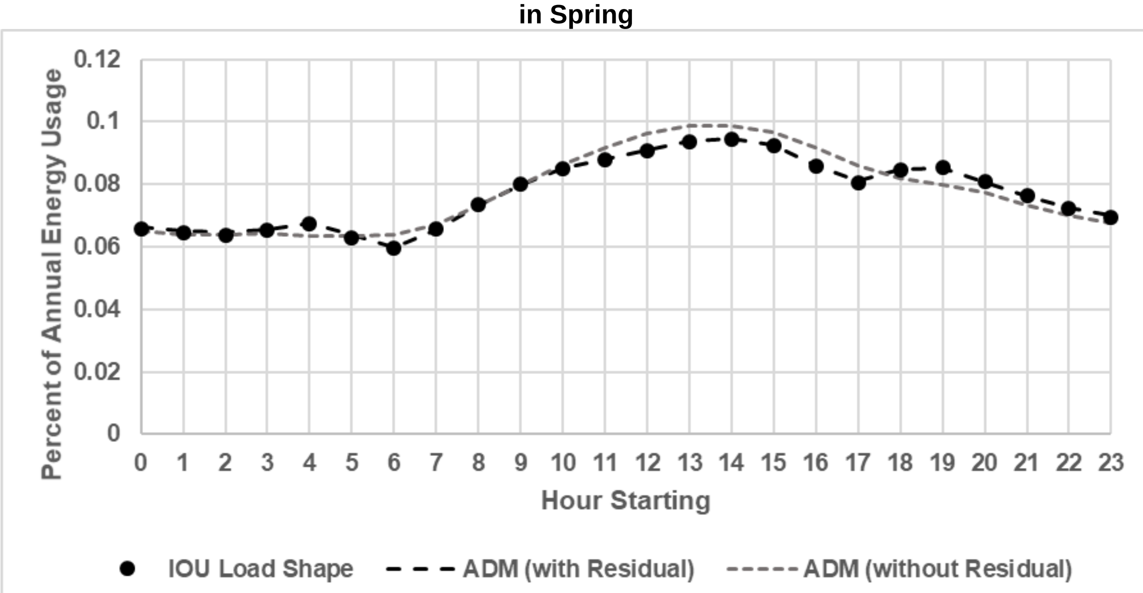
Figure 160: Comparison of the Average Daily Weekday Profile With and Without Residual in Spring



A comparison of the average daily load shape in weekdays in spring at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

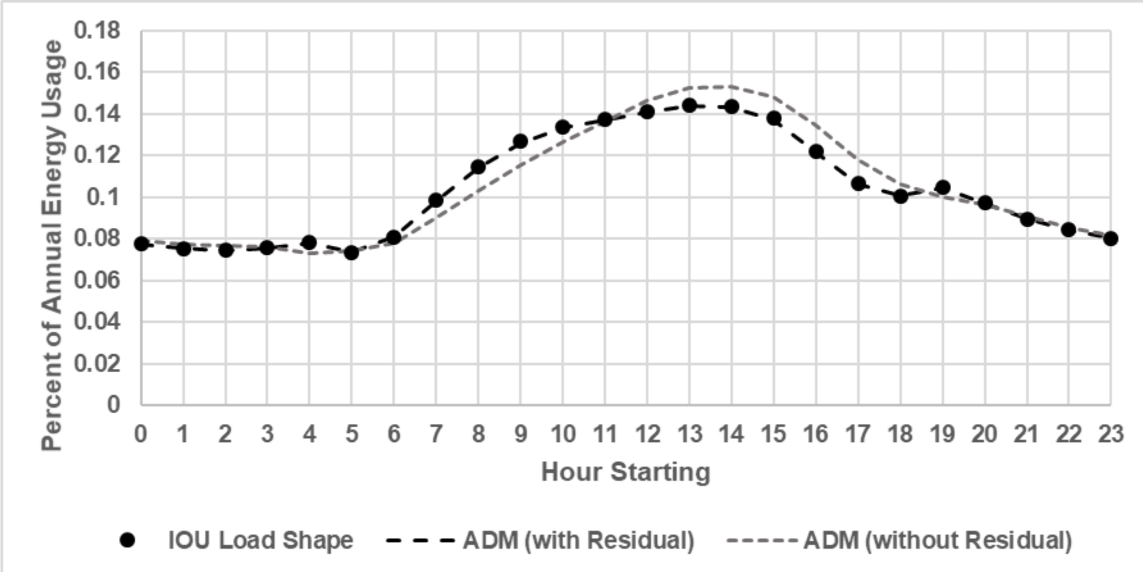
Figure 161: Comparison of the Average Daily Weekend Profile With and Without Residual in Spring



A comparison of the average daily load shape in weekends in spring at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

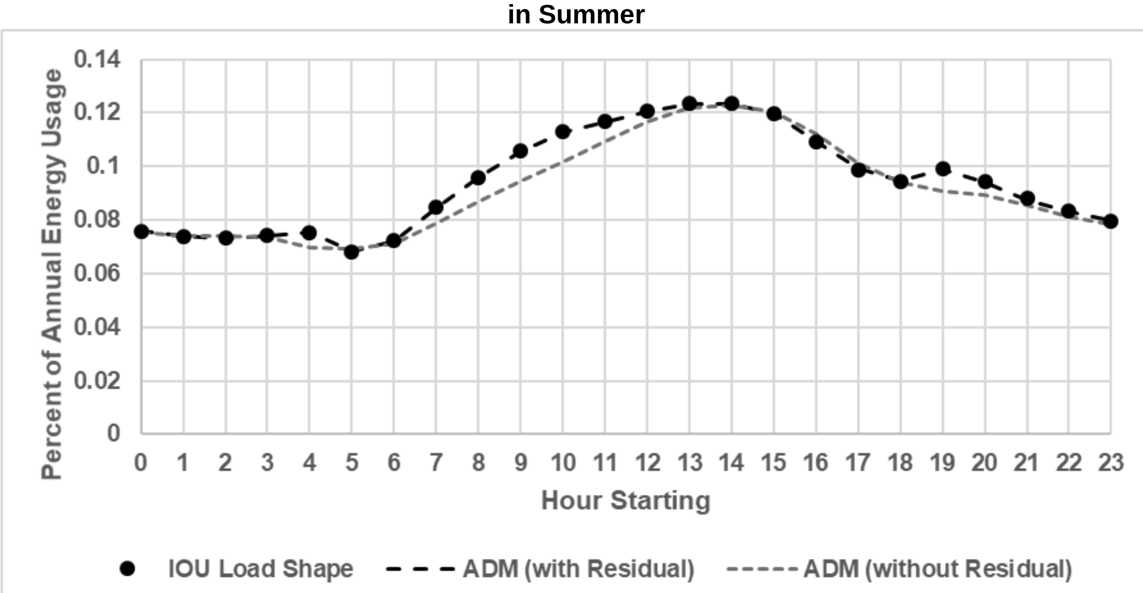
Figure 162: Comparison of the Average Daily Weekday Profile With and Without Residual in Summer



A comparison of the average daily load shape in weekdays in summer at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

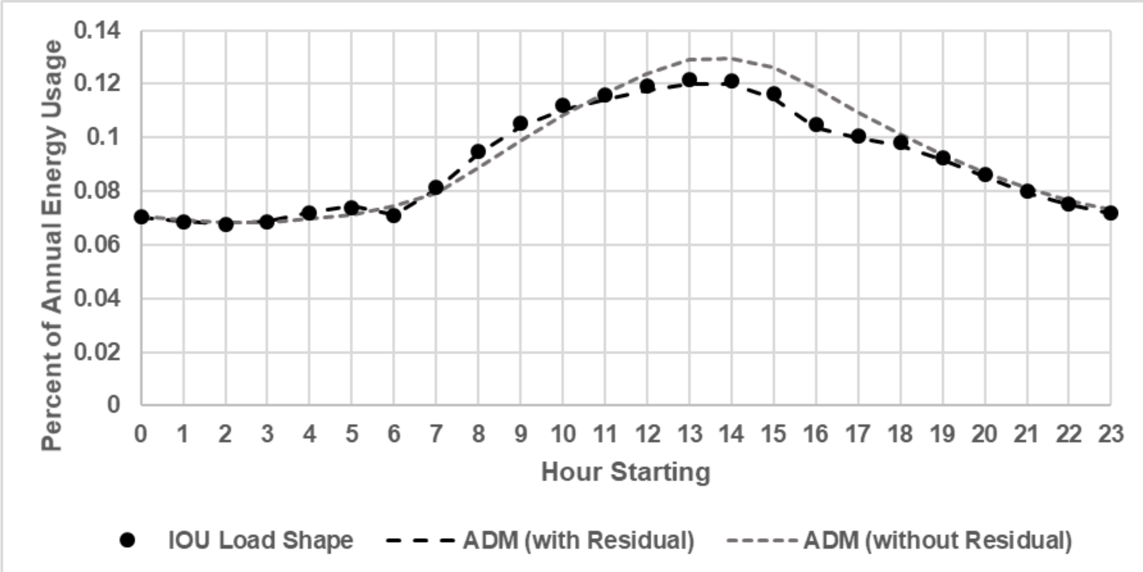
Figure 163: Comparison of the Average Daily Weekend Profile With and Without Residual in Summer



A comparison of the average daily load shape in weekends in summer at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

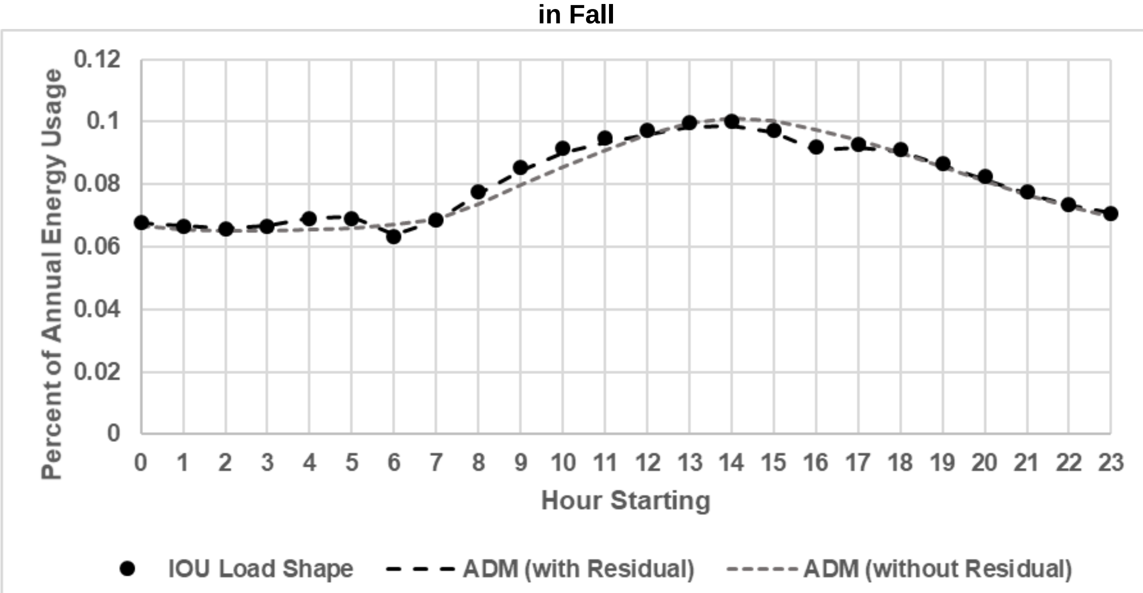
Figure 164: Comparison of the Average Daily Weekday Profile With and Without Residual in Fall



A comparison of the average daily load shape in weekdays in fall at the whole building level with and without application of the residual load shape.

Source: ADM Associates, Inc.

Figure 165: Comparison of the Average Daily Weekend Profile With and Without Residual in Fall



A comparison of the average daily load shape in weekends in fall at the whole building level with and without application of the residual load shape.

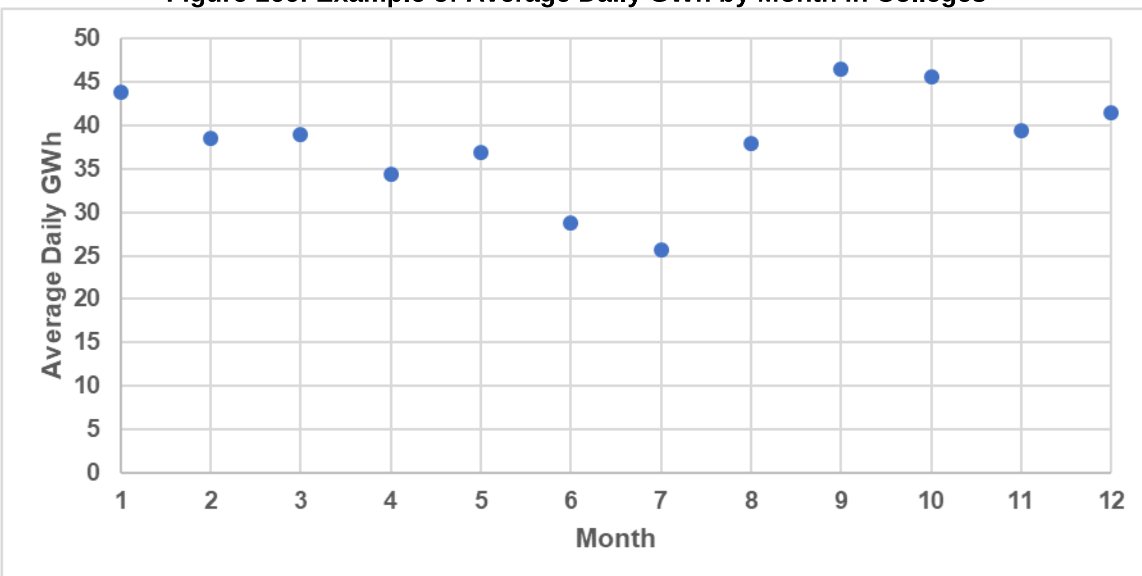
Source: ADM Associates, Inc.

Adjustments for Schools/Colleges

Unlike the ten other commercial building types, colleges and schools generally do not operate on a year-round basis. This reduced operation is apparent when reviewing the AMI data in a given forecast zone.

Figure 166 provides an example of the average daily energy use for colleges in a given forecast zone in the year 2014. The average daily energy use significantly reduces in the summer months, although summer in other commercial building types is typically hallmarked by higher energy use due to the presence of cooling load.

Figure 166: Example of Average Daily GWh by Month in Colleges



An example of the average daily GWh by month for all colleges in a single forecast zone.

Source: ADM Associates, Inc.

Although the daily profiles in the summer months represent a reduction in sector-level energy use, ADM cannot attribute this reduction solely to the absence of end-use loads altogether. Rather, because ADM is modeling the average profile across all buildings in a given forecast zone, there will still be a portion of buildings active and contributing to the load during these periods of low energy use. Additionally, although EnergyPlus has the capacity to model accurate load shapes relative to a specified weather profile, it is difficult to model load shapes in the summer months as the change in the load shape in the summer month is more or less a reduction in the intensity of the curve rather than a change in the cooling set point schedule, which would ultimately reduce the summer load by changing the cooling profile instead of keeping its profile and reducing its magnitude.

Therefore, ADM elected to adjust the intensity of the heating, cooling, and ventilation load shapes for colleges and schools analytically instead of adjusting them as part of the EnergyPlus framework. ADM first began by generating 8,760 load shapes for the non-HVAC loads using the end-use load shapes.[5] These load shapes were then scaled according to the 2014, 2015, and 2016 GWh specified in the Commercial Building Energy Demand Forecast Model. Similarly, the AMI data for each building type for each year for each forecast zone was scaled to the corresponding total GWh for 2014, 2015, and 2016, respectively. ADM then took the difference between the scaled AMI data and the modeled non-HVAC end-uses. This difference was assumed to be the energy usage attributable to the three HVAC loads. ADM used this baseline-subtracted HVAC load shape to create a series of scalars with which ADM could then increase or decrease the intensity of the EnergyPlus-modeled HVAC load shapes.

To begin doing this, ADM generated 8,760 load shapes for heating, cooling, and ventilation for 2014, 2015, and 2016 using the smoothed and compressed coefficients.[6] These profiles were scaled to their respective GWh values as predicted by the Commercial Building Energy Demand Forecast Model and aggregated together to create an overall "HVAC" load shape for 2014, 2015, and 2016. ADM aggregated across the three HVAC load shapes because ADM could not assume which proportion of the baseline-subtracted HVAC load belongs to each of the three end-uses. Additionally, there is significant overlap between the heating and cooling season in commercial space, as cooling will tend to run all year round while heating will be isolated to a specific time of year. Therefore, to maintain a conservative approach, ADM created scalars for HVAC aggregated across heating, cooling, and ventilation and applied the same scalars to all three load shapes.

The baseline-subtracted HVAC profile provides several avenues for potentially correcting the modeled HVAC load shapes. ADM now has a baseline-subtracted HVAC profile at an 8,760 resolution. Although ADM could use said profile to make 8,760-level adjustments to the heating, cooling, and ventilation load shapes, there is a margin of error associated with each observation in the 8,760-load shape. If ADM assumes that this error is distributed randomly across the 8,760 profile, the margin of error for a single point estimation should reduce as ADM works in higher resolutions. Thus, while error persist at an hourly resolution, that error should begin to cancel itself out as higher resolutions of data are reviewed such as at a daily level, etc. Furthermore, although ADM could manipulate the heating, cooling, and ventilation load shapes relative to the 8,760 baseline-subtracted profile, ADM cannot know the relationship in the 8,760 baseline-subtracted profile and the three underlying end-uses and modifying the modeled end-uses may result in inappropriate changes to the load shapes.

As a compromise, ADM created scalars that changed the intensity of the modeled load shapes compared to the baseline-subtracted profiles at a month by weekday level. To

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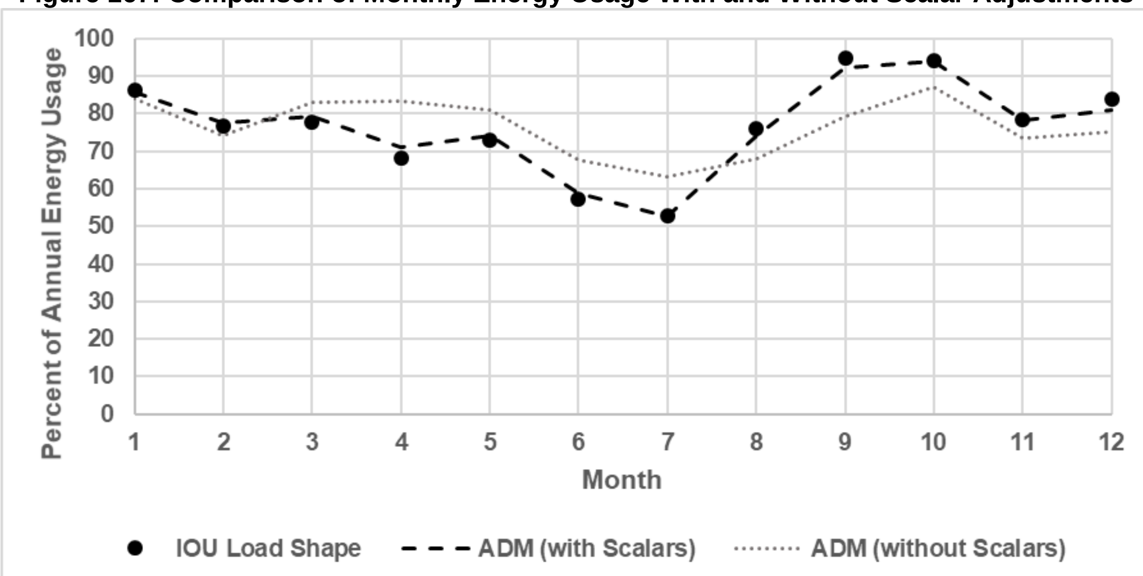
5 The generation of the HVAC coefficients is detailed in the "Post Calibration Modeling" section beginning on page 118.

create these scalars, ADM aggregated the baseline-subtracted profiles and the modeled HVAC profile by taking the sum of the GWh for each month and weekday/weekend. A scalar was then generated by dividing the baseline-subtracted GWh values by the corresponding modeled HVAC GWh. This results in a series of 24 scalars that can then be used to modify the coefficients stored for the heating, cooling, and ventilation load shapes. ADM then reviewed the scalars for each building and made additional adjustments to the monthly intensity of HVAC and non-HVAC loads when deemed appropriate.

Figure 167 through Figure 175 provide examples of a school in a given forecast zone with and without scalar adjustment.

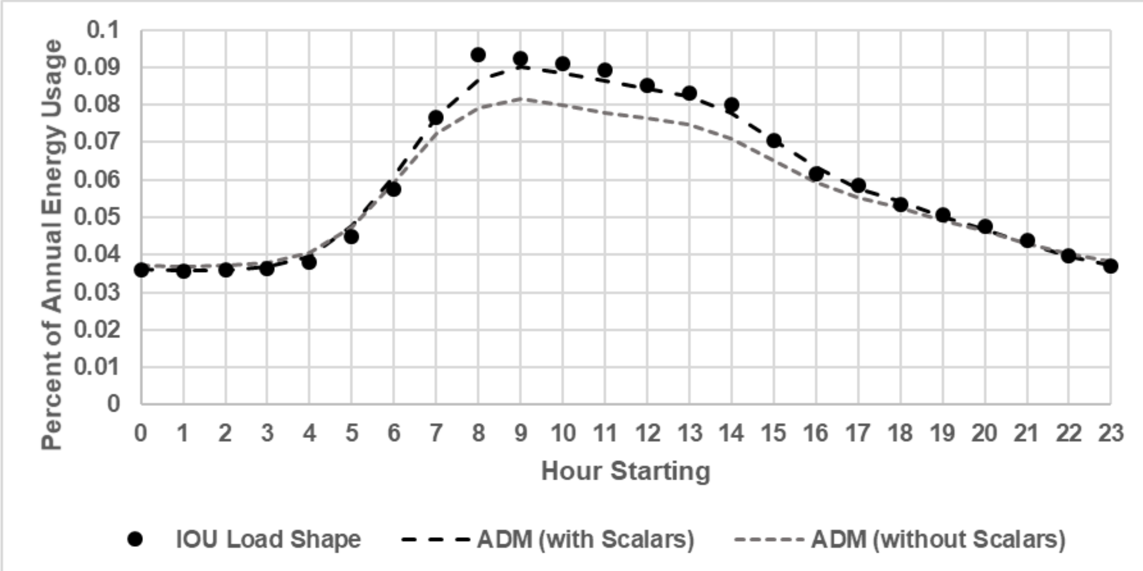
Figure 167: Comparison of Monthly Energy Usage With and Without Scalar Adjustments



A comparison of the monthly energy usage at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

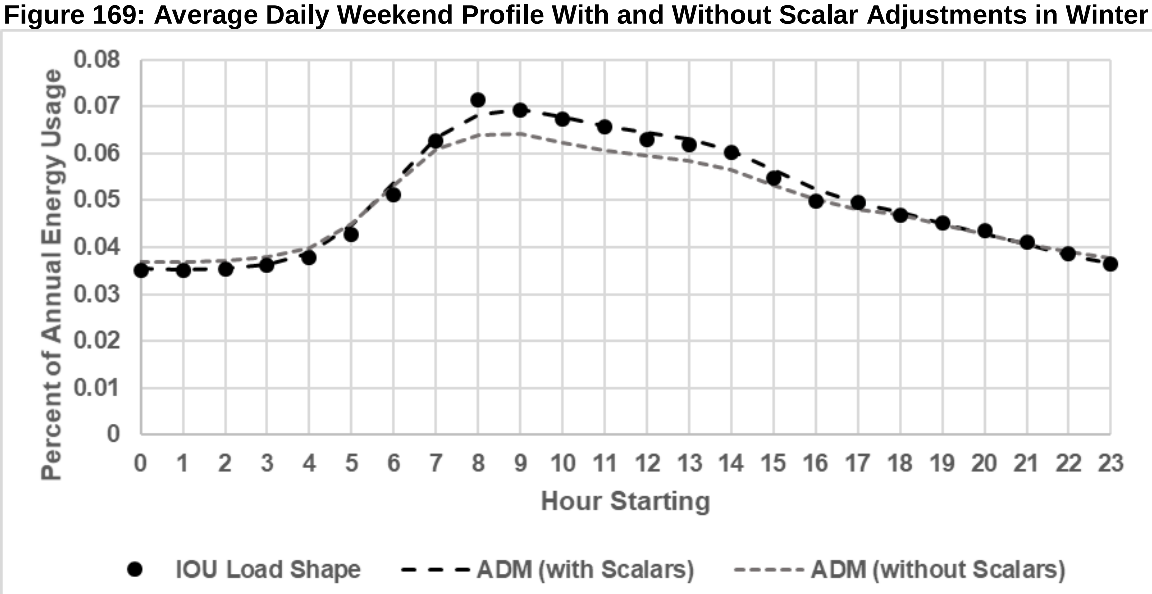
Figure 168: Average Daily Weekday Profile With and Without Scalar Adjustments in Winter



A comparison of the average daily load shape in weekdays in winter at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

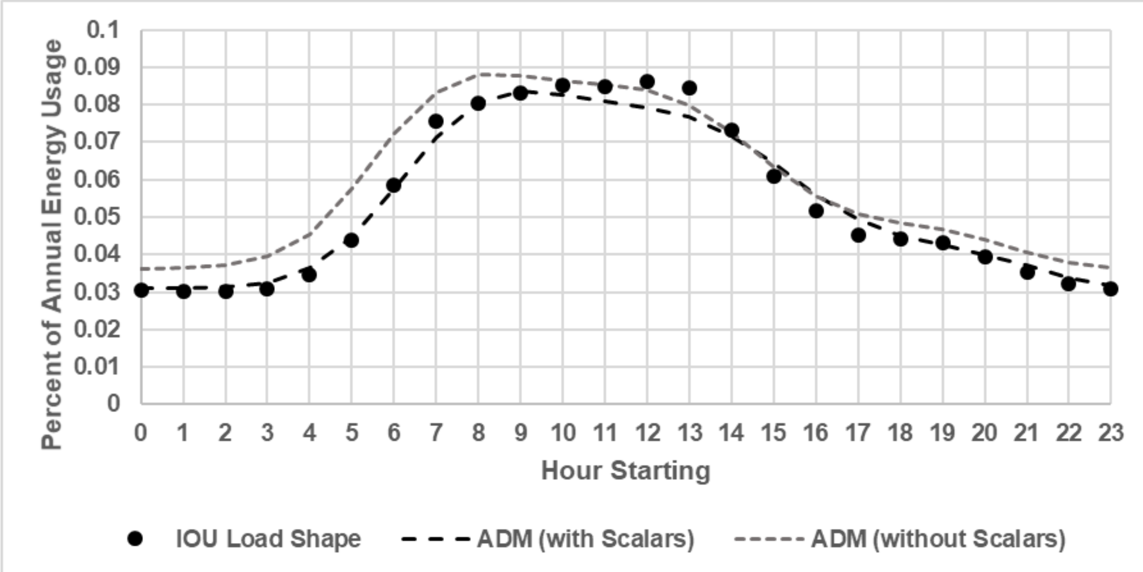
Figure 169: Average Daily Weekend Profile With and Without Scalar Adjustments in Winter



A comparison of the average daily load shape in weekends in winter at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

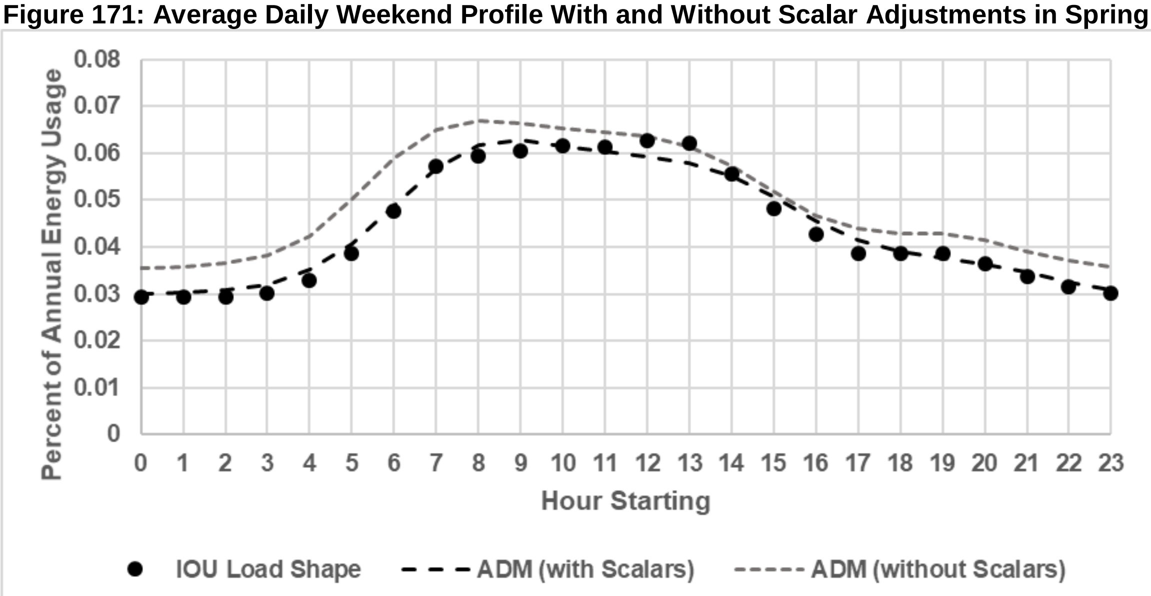
Figure 170: Average Daily Weekday Profile With and Without Scalar Adjustments in Spring



A comparison of the average daily load shape in weekdays in spring at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

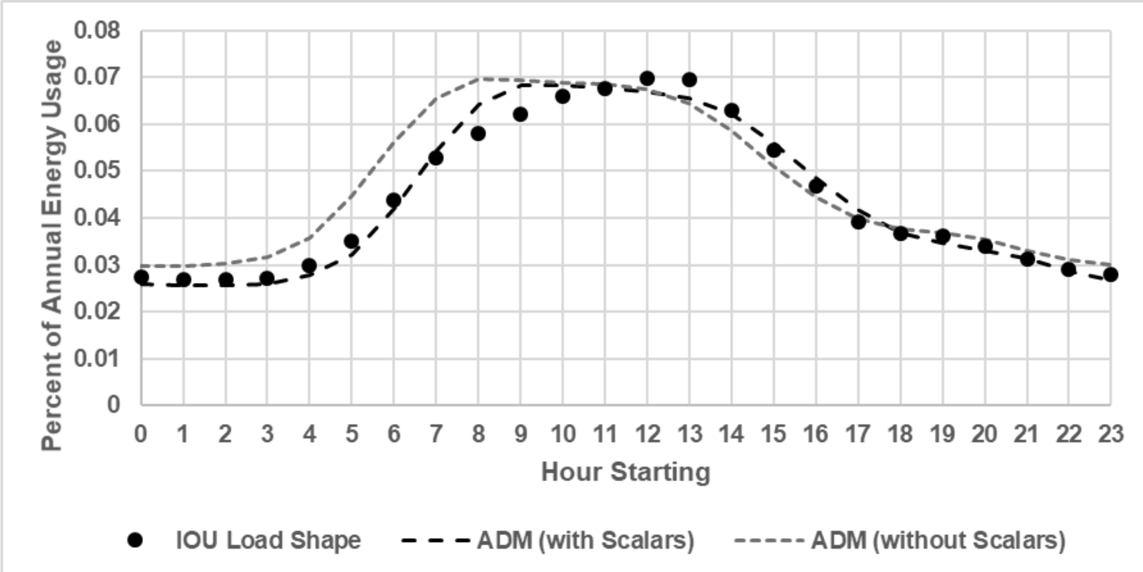
Figure 171: Average Daily Weekend Profile With and Without Scalar Adjustments in Spring



A comparison of the average daily load shape in weekends in spring at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

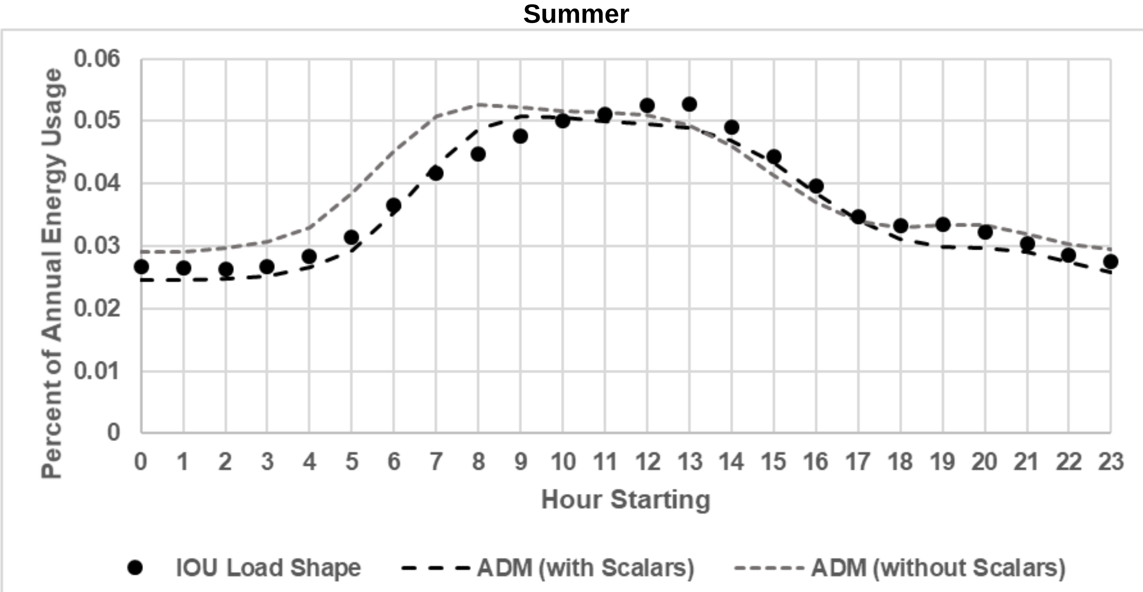
Figure 172: Average Daily Weekday Profile With and Without Scalar Adjustments in Summer



A comparison of the average daily load shape in weekdays in summer at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

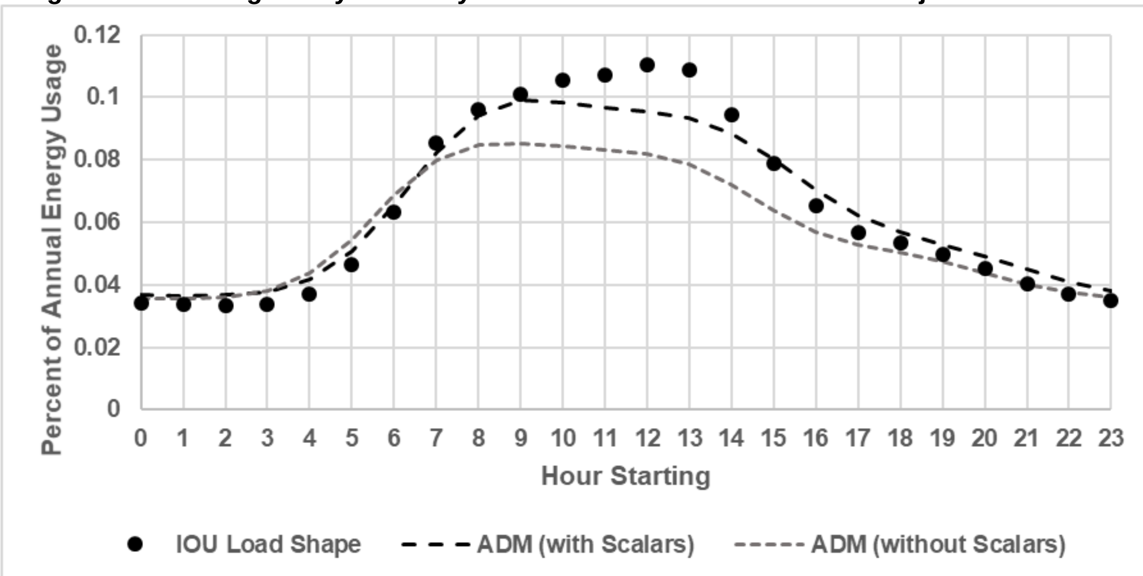
Figure 173: Average Daily Weekend Profile With and Without Scalar Adjustments in Summer



A comparison of the average daily load shape in weekends in summer at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

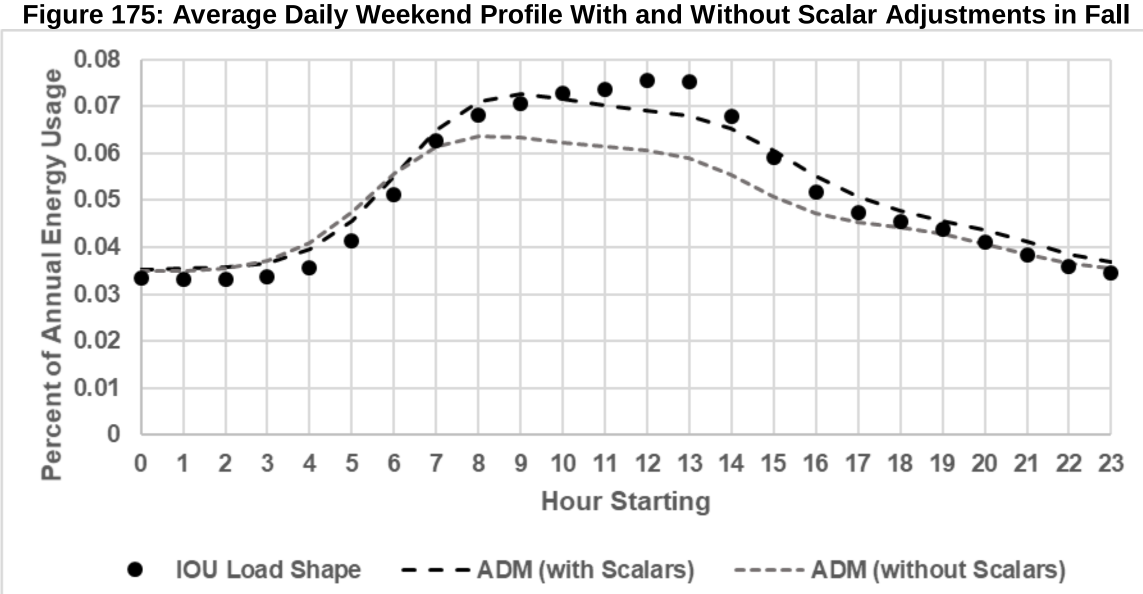
Figure 174: Average Daily Weekday Profile With and Without Scalar Adjustments in Fall



A comparison of the average daily load shape in weekdays in fall at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

Figure 175: Average Daily Weekend Profile With and Without Scalar Adjustments in Fall



A comparison of the average daily load shape in weekends in fall at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

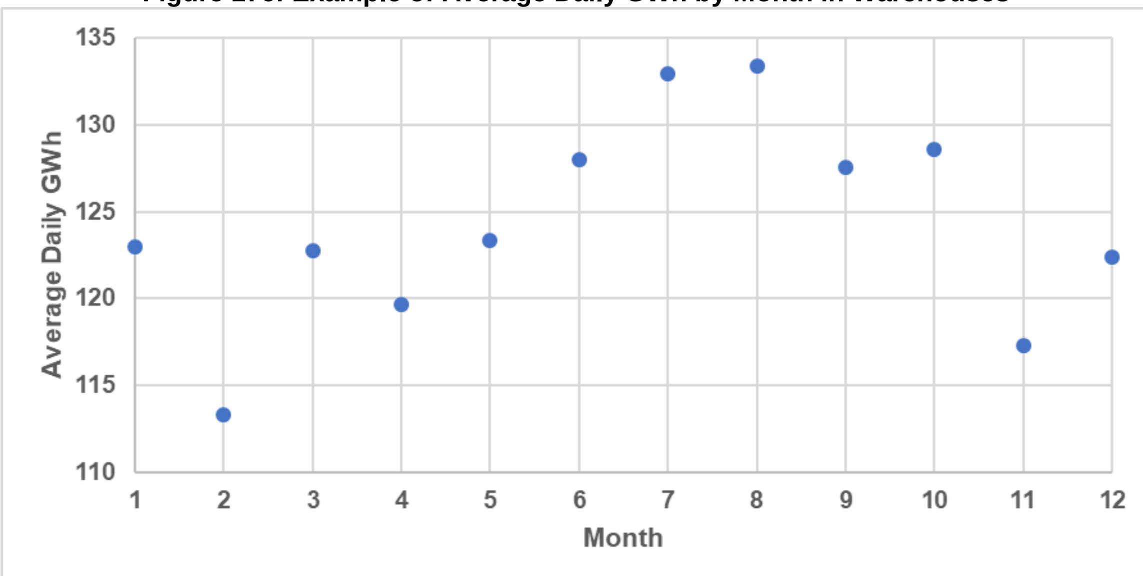
Source: ADM Associates, Inc.

Adjustments to Capture Unique Characteristics by Zone

Although the internal load shapes for the commercial sector were sourced from the CEUS (Itron, Inc. 2006) and modified relative to the average 24-hour profile for each weekday in the shoulder season, it is important to note that by doing this, ADM assumes that the intensity of the load shape remains constant throughout the year. Furthermore, because of changes to forecast zone assignment between 2006 and present, ADM are unable to generate internal load shapes that vary at a forecast zone level. Instead, the internal load shapes are generated at an IOU level. However, the AMI data shows that both assumptions may not be accurate, as evidenced by

Figure 176.

Figure 176: Example of Average Daily GWh by Month in Warehouses



An example of the average daily GWh by month for all warehouses in a single forecast zone.

Source: ADM Associates, Inc.

This figure provides an example of the average monthly energy usage for warehouses in a given forecast zone. Cooling represents less than 5% of the total annual electricity usage, as predicted by the Commercial Building Energy Demand Forecast Model. Despite the relatively low impact of cooling, however, one can see significant peaked-ness during the summer months in the example, above and beyond the expected peaked-ness given the saturation of cooling. Furthermore, the forecast zones differ from one another relative to when that peaked-ness occurs.

One way to correct for this forecast zone-specific seasonality can be to take advantage of the residual load shape. As noted previously, the residual load shape is constructed out of three major components: a CDH component, an HDH component, and a flat component. These three components are generated at a month x day-type x hour level. ADM can assume that if the seasonality is driven solely by the month of the year rather than explicitly by weather, the flat component of the residual load shape should represent the difference between the modeled non-HVAC components and the true non-HVAC load.

Using a method like the method used to adjust HVAC load shapes for schools and colleges on page 131, ADM created scalars to modify the non-HVAC load shapes for all building types for the years 2014, 2015, and 2016. ADM first began by reconstituting only the flat component of the residual load shape for each building for each forecast zone and scaling the load to the appropriate GWh value. Similarly, ADM generated 8,760 load shapes for the non-HVAC loads using the end-use load shapes modeled in previously in this chapter. These load shapes were then scaled according to the 2014, 2015, and 2016 GWh specified in the Commercial Building Energy Demand Forecast Model. ADM then aggregated the profiles into two consolidated profiles: the modeled non-HVAC load shape, which is the aggregation of all non-HVAC loads; and the modeled profile with flat residual, which aggregated all non-HVAC loads and the modeled flat component of the residual.

Theoretically, the modeled profile with flat residual should represent the corrected model of all non-HVAC load shapes at an 8,760 resolution for each of the three base years. However, there is a margin of error associated with each observation in the 8,760-load shape. If one assumes that this error is distributed randomly across the 8,760 profile, the margin of error for a single point estimation should reduce as data is aggregated to higher resolutions. Thus, while error may be persistent at an hourly resolution, that error should begin to cancel itself out as one moves to looking at data on a daily level, etc. Furthermore, although ADM could manipulate the non-HVAC load shapes relative to the 8,760 baseline-subtracted profile, ADM cannot know the relationship in the 8,760 baseline-subtracted profile and the underlying end-uses and modifying the modeled end-uses may result in inappropriate changes to the load shapes.

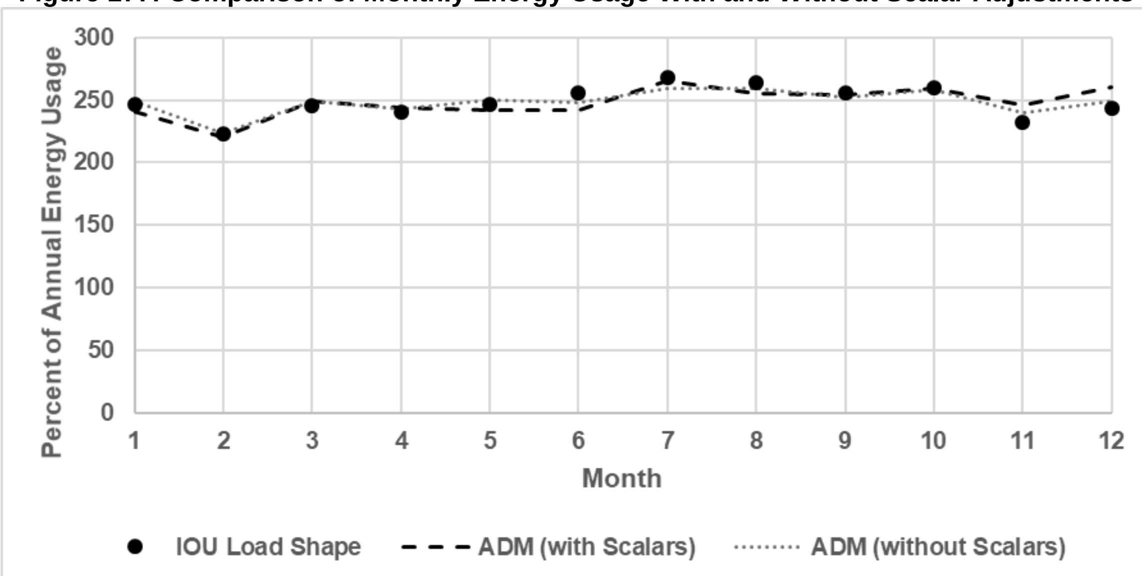
As a compromise, ADM created scalars that changed the intensity of the internal load shapes as a function of either month or month by weekday. The goal, ultimately, was to create a series of scalars to transform the total monthly energy use modeled via the coefficients to consistently predict total monthly energy usage that was in line with the version of the load shape that had the flat-residual applied. To accomplish this, ADM created a monthly and a month x weekday scalar by aggregating the total energy for the flat-residual applied and unapplied profile at either the monthly or month x weekday level and dividing the flat-residual applied value by the unapplied value.

ADM then determined which set of scalars would be the most appropriate for each forecast zone and building type: un-scaled, scaled by month, or scaled by month and weekday. ADM did this by comparing the NRMSE before and after the application of each scalar types and selecting the scalar values which provided the greatest reduction in model error. ADM then modified and stored the coefficients for each non-HVAC load shape by applying the appropriate scalar for each month or each month x weekday.

Figure 177 through

Figure 185 provide examples of Warehouses in a given forecast zone with and without scalar adjustment.

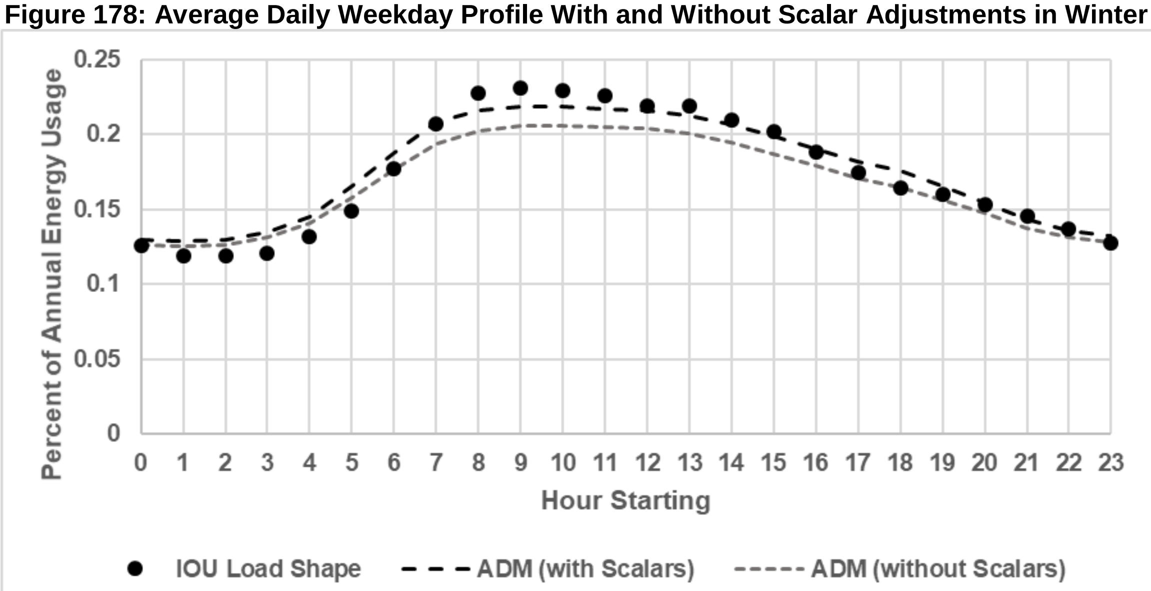
Figure 177: Comparison of Monthly Energy Usage With and Without Scalar Adjustments



A comparison of the monthly energy usage at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

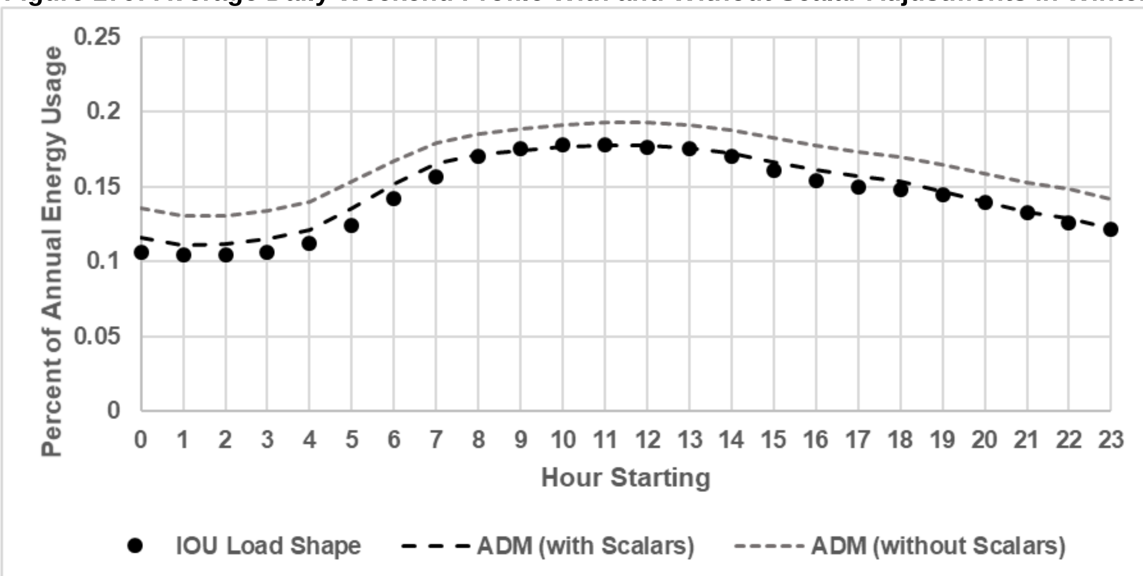
Figure 178: Average Daily Weekday Profile With and Without Scalar Adjustments in Winter



A comparison of the average daily load shape in weekdays in winter at the whole building with and without application of the month x day scalars, prior to application of the residual load shape.

Source: ADM Associates, Inc.

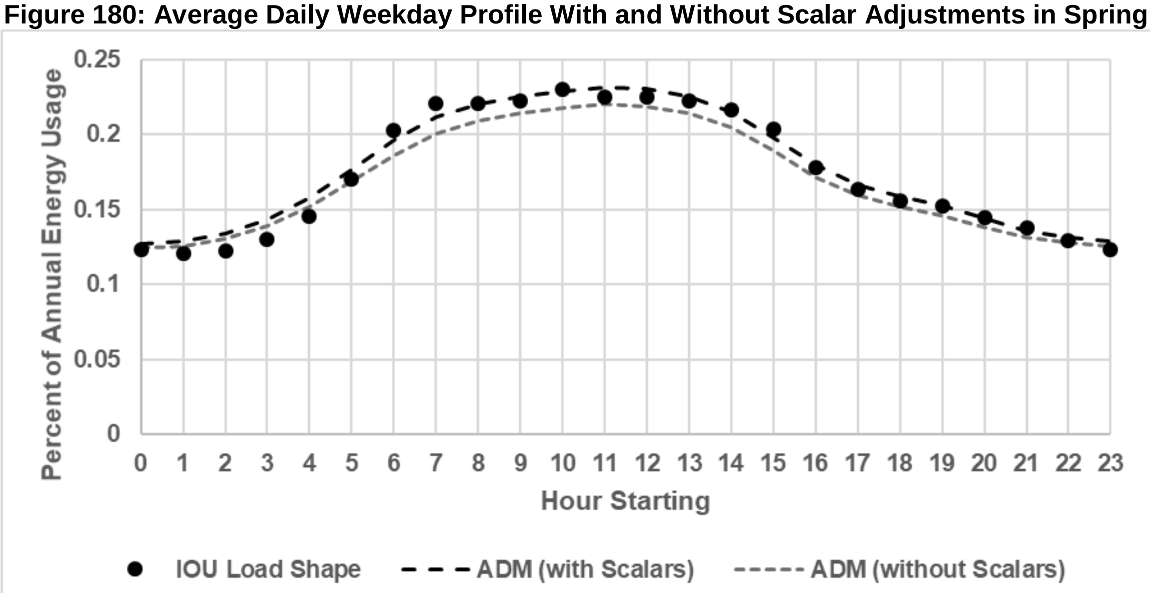
Figure 179: Average Daily Weekend Profile With and Without Scalar Adjustments in Winter



A comparison of the average daily load shape in weekends in winter at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

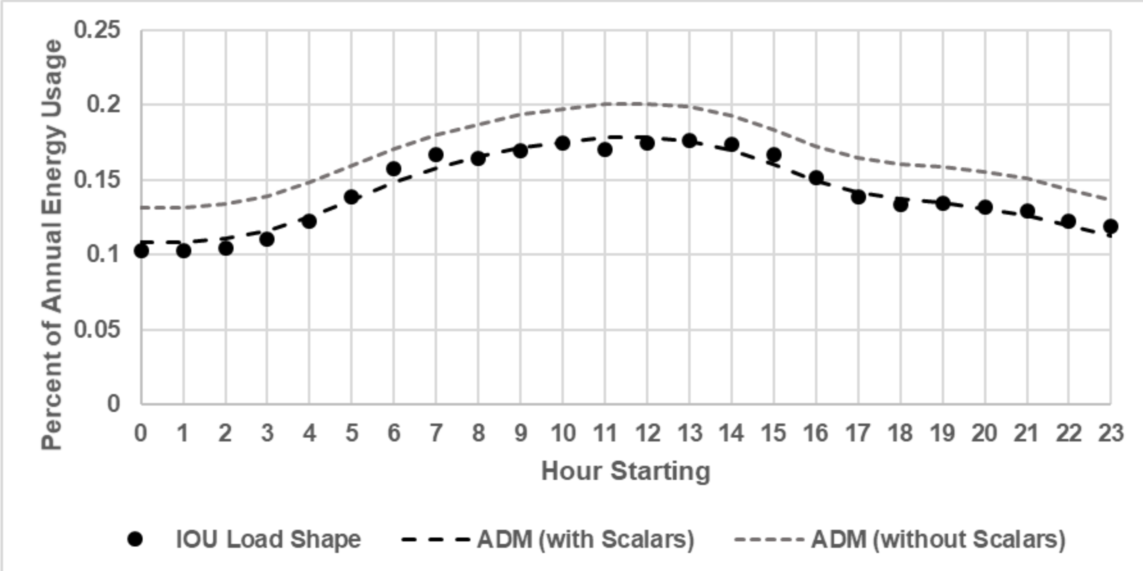
Figure 180: Average Daily Weekday Profile With and Without Scalar Adjustments in Spring



A comparison of the average daily load shape in weekdays in spring at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

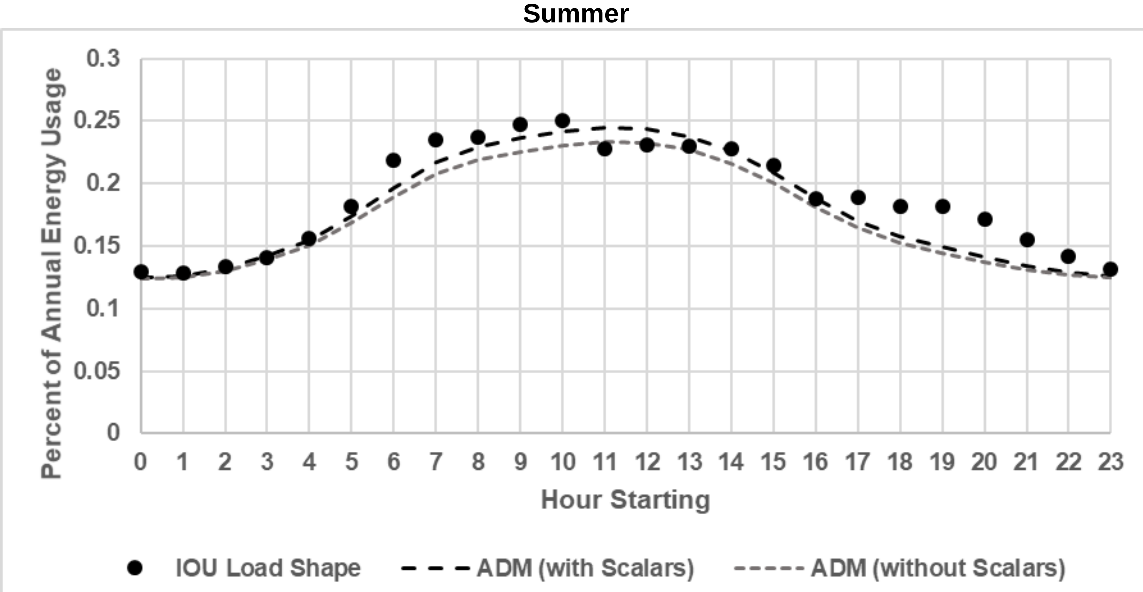
Figure 181: Average Daily Weekend Profile With and Without Scalar Adjustments in Spring



A comparison of the average daily load shape in weekends in spring at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

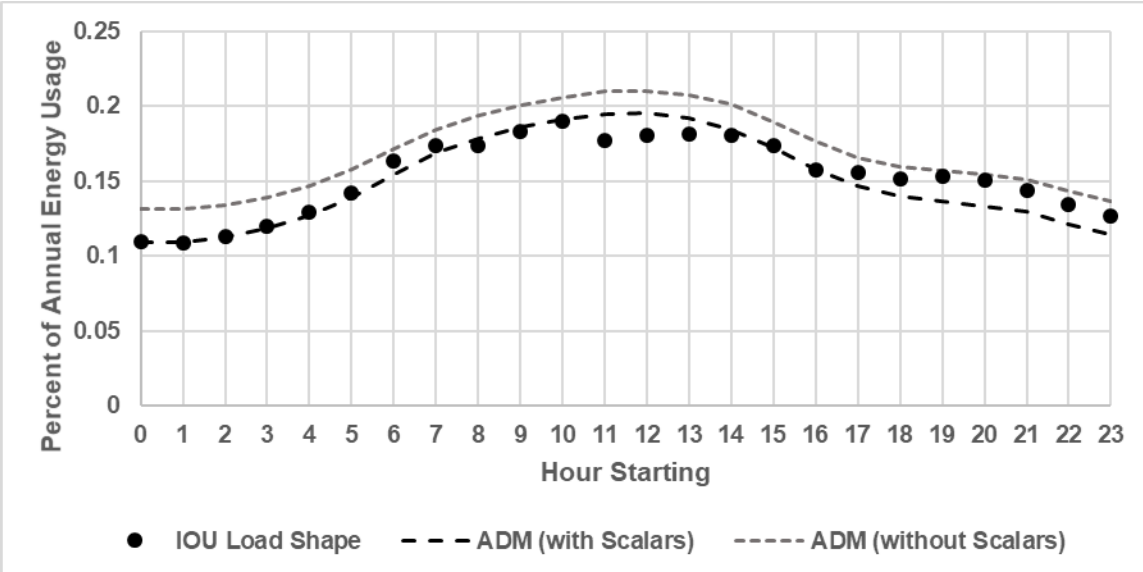
Figure 182: Average Daily Weekday Profile With and Without Scalar Adjustments in Summer



A comparison of the average daily load shape in weekdays in summer at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

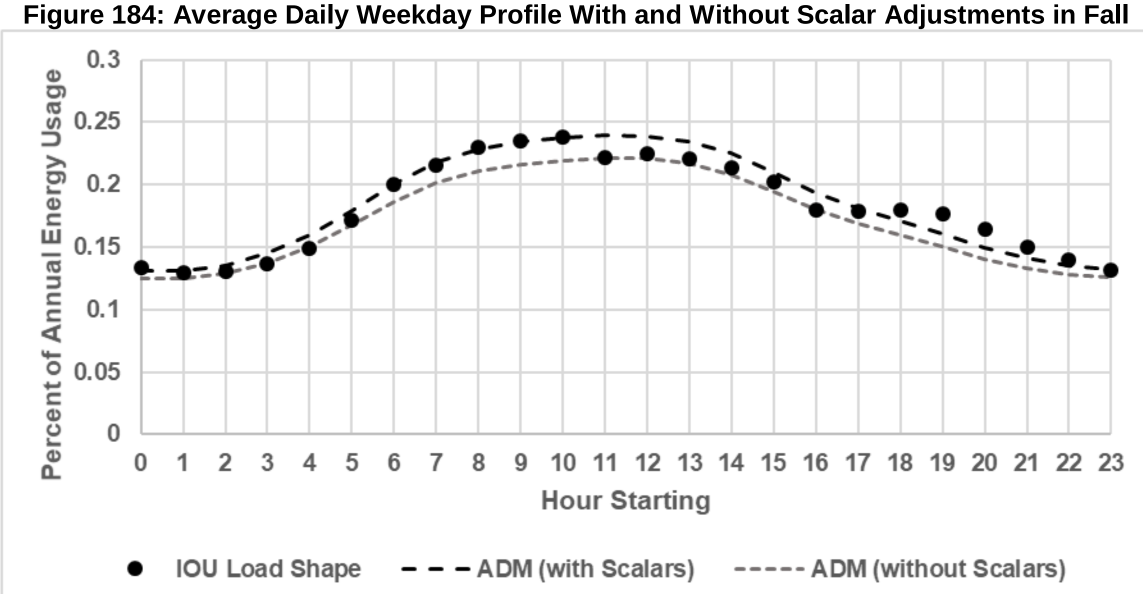
Figure 183: Average Daily Weekend Profile With and Without Scalar Adjustments in Summer



A comparison of the average daily load shape in weekends in summer at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

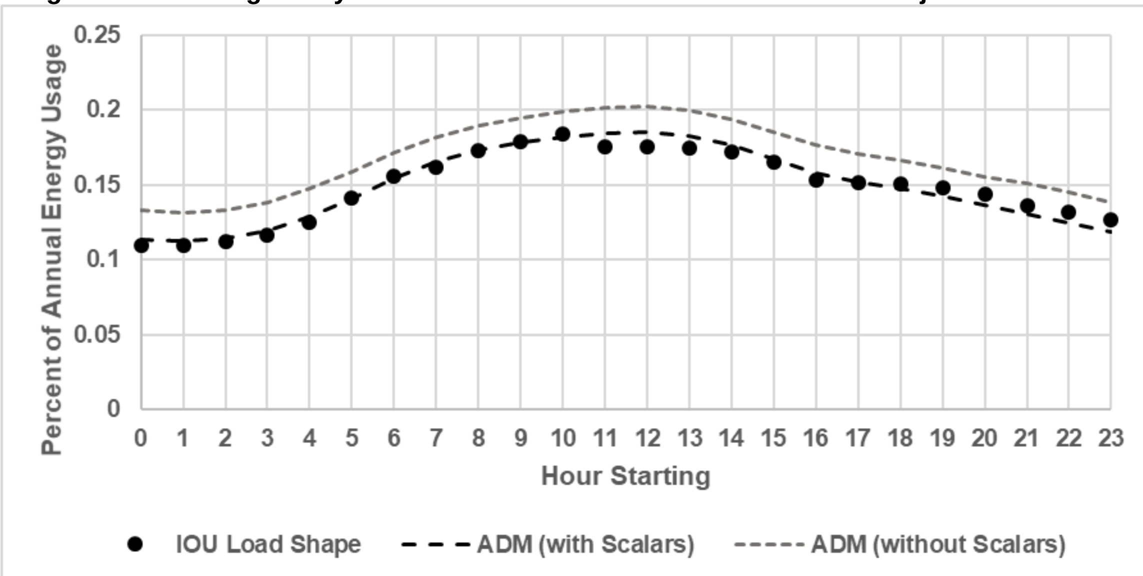
Figure 184: Average Daily Weekday Profile With and Without Scalar Adjustments in Fall



A comparison of the average daily load shape in weekdays in fall at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

Figure 185: Average Daily Weekend Profile With and Without Scalar Adjustments in Fall



A comparison of the average daily load shape in weekends in fall at the whole building level with and without application of the month x day scalars but prior to application of the residual load shape.

Source: ADM Associates, Inc.

CHAPTER 4: Base Load Shapes: Agricultural Sector

Unlike the commercial and residential sectors, the Energy Commission's agricultural load shapes are not currently generated at the end-use level. Rather, load shapes are currently isolated to the facility-type only. Energy demand in the agriculture sector tends to be process-driven, i.e., the load shape for irrigation is primarily driven by the underlying process and thus most end-uses are also tied to that essential load shape.

There are four facility types represented in the agricultural sector:

- Crops
- Irrigation
- Livestock
- Water Supply

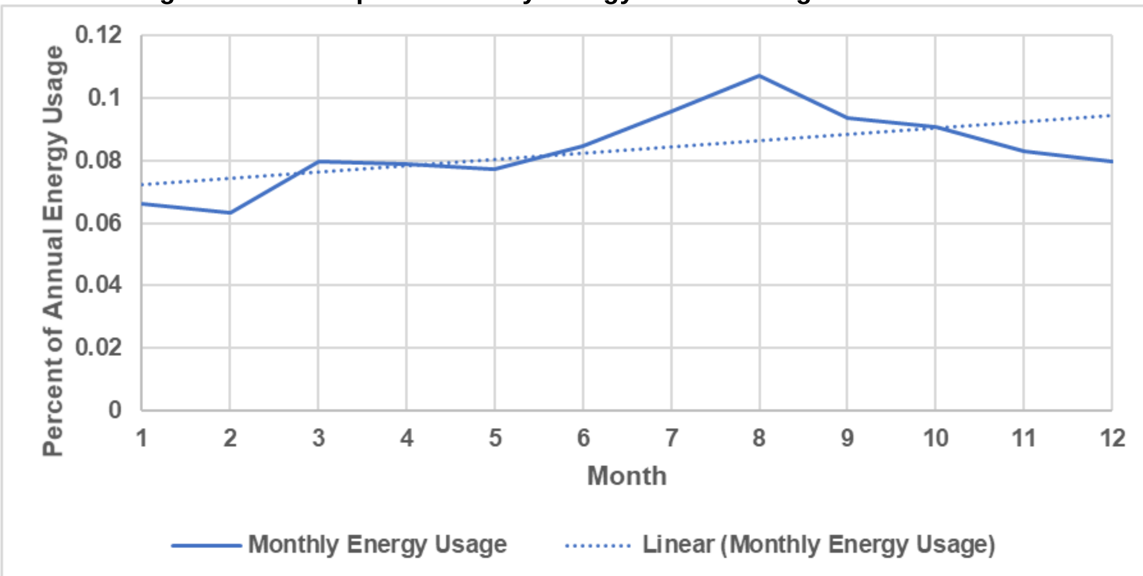
ADM's primary goal for the agricultural sector was to use the AMI data submitted by the three California IOUs to create a set of coefficients which accurately reflect the typical load shape for each facility type in each forecast zone and can be used to generate an 8,760-hour load shape for any given year. The remainder of this chapter will describe the methodology for generating said coefficients.

Regression Modeling

To generate sets of coefficients that represent every facility type for every forecast zone, ADM relied on a regression-based algorithm based on a linear CDH regression model. Initial considerations were made to determine whether a compression of the data to a simple 12-month x 24-hour x 8-day matrix would be sufficient for modeling non-commercial/non-residential sectors. However, visual inspection of the monthly load shapes shows some variability over a calendar year.

Figure 186 illustrates this seasonality, with highest energy use during the summer months and lower energy use in the winter and shoulder seasons.

Figure 186: Example of Monthly Energy Use in the Agricultural Sector



Example of monthly energy use in an Industrial facility-type as taken from across an agricultural facility-type in a single forecast zone in the 2015 base year.

Source: ADM Associates, Inc.

Because of the seasonal nature of energy use, ADM elected to include a temperature-based term in the regression equation. Although it is unlikely that the increase in energy usage during the summer is tied specifically to HVAC, CDH can be used to approximate variables that are collinear to weather, such as length of day, seasonal production, etc. ADM opted to use a CDH term rather than an hourly temperature value to mitigate potential sensitivity as temperature values reach extreme hot or extreme cold values. Using a CDH variable ensures that as the temperature dips towards negative values, the term associated with the weather variable cannot become negative.

In addition to the apparent seasonality present in the AMI data, ADM also noted significant load growth in the AMI data. There is a significant linear relationship between monthly energy usage and the number of months since the origin point (in this case, the origin being January of 2015). Therefore, ADM included a "day of year" term (with 1 representing January 1st) in the regression equation to include a term to capture the observed linear growth. Although ADM assumed that linear growth will continue to be present going forward, should someone want to exclude linear growth from a generated load shape, modeling the effect as part of the regression allows one to do so.

In addition to the main effects described above, ADM also expected the load to vary relative to weekday type (Sunday-Saturday and observed holidays) and hour of day. Furthermore, although scheduled loads should theoretically shift in accordance with daylight savings time, in real-world scenarios, some loads tend to shift relative to daylight savings time, while other loads end up remaining constant. Thus, ADM also considered whether an observation fell into PST or PDT an additional main effect for the models. Although the temporal main effects described in this paragraph could be modeled in a consolidated regression with appropriate interactive terms, ADM opted to segment the data set by the three temporal criteria (PST/PDT, weekday, and hour). This yields mathematically identical results while evades computational resource constraints.

After segmenting the data, each segment of data was then run through the following regression model:

$$y = \beta_0 + \beta_1 \cdot CDH + \beta_2 \cdot Day\ of\ Year + \varepsilon$$

Where:

- y is the predicted kW of the building
- β_0 is the intercept
- β_1 is the CDH weight
- β_2 is the linear growth term relative of the day of year (1-365 or 366)
- ε is the error term.

The model was run for each data segment and the regression coefficients recorded for use in the load shape generator.

To select an appropriate CDH base term, ADM iterated through five potential CDH base values (50 degrees Fahrenheit, 55 degrees Fahrenheit, 60 degrees Fahrenheit, 65 degrees Fahrenheit, and 70 degrees Fahrenheit) to determine which value provided the lowest amount of model error, as represented through NRMSE.[7]

Data Sources

The following section provides a list of the data sources used to generate the agricultural load shapes. In addition to listing the data source, a brief description of the data source and any data preparation activities are provided.

AMI Data

As part of this project, a data request was submitted to the IOUs requesting data for all non-residential sectors from the years 2014, 2015, and 2016. In response to this data request, the IOUs provided averaged hourly data by building sub-type and either usage level (PG&E and SDG&E segmented data by high, medium, and low users) or rate class (SCE).

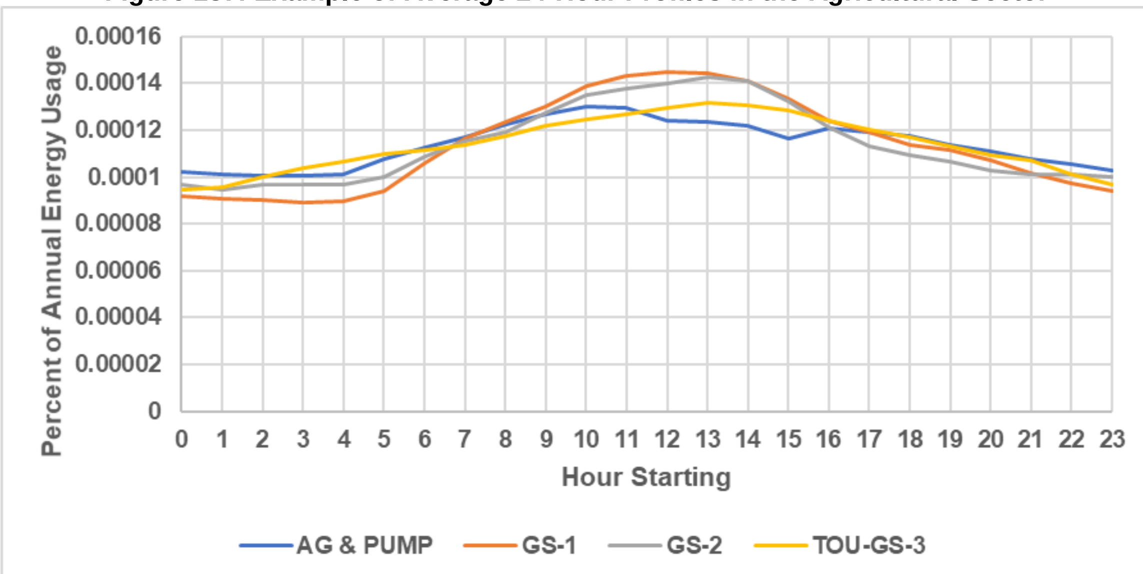
Prior to using the interval meter data, ADM first pre-treated all data. This pre-treatment consisted of standardizing the nomenclature of all files and merging the dataset with climate-zone specific hourly historical weather data obtained from the Energy Commission. Hourly timestamps were standardized to units of PST for the entire year

7 The equation for calculating NRMSE is previously defined in the “Post Calibration Modeling” section of the Commercial chapter, beginning on page 118.

(i.e., 11 p.m. PDT was standardized to 10 p.m. PST). Data was restricted to January 1, 2014 through December 31, 2016.

As part of the data validation process, ADM reviewed the data provided by the IOUs. ADM reviewed data for gaps and significant spikes within the data over the year. In some cases, ADM noticed jagged-ness, atypical gaps, or convergence of different rate class profiles. Figure 187 presents an example of the average hourly profiles at different rate classes for a single facility type in a single forecast zone in the agricultural sector.

Figure 187: Example of Average 24-Hour Profiles in the Agricultural Sector



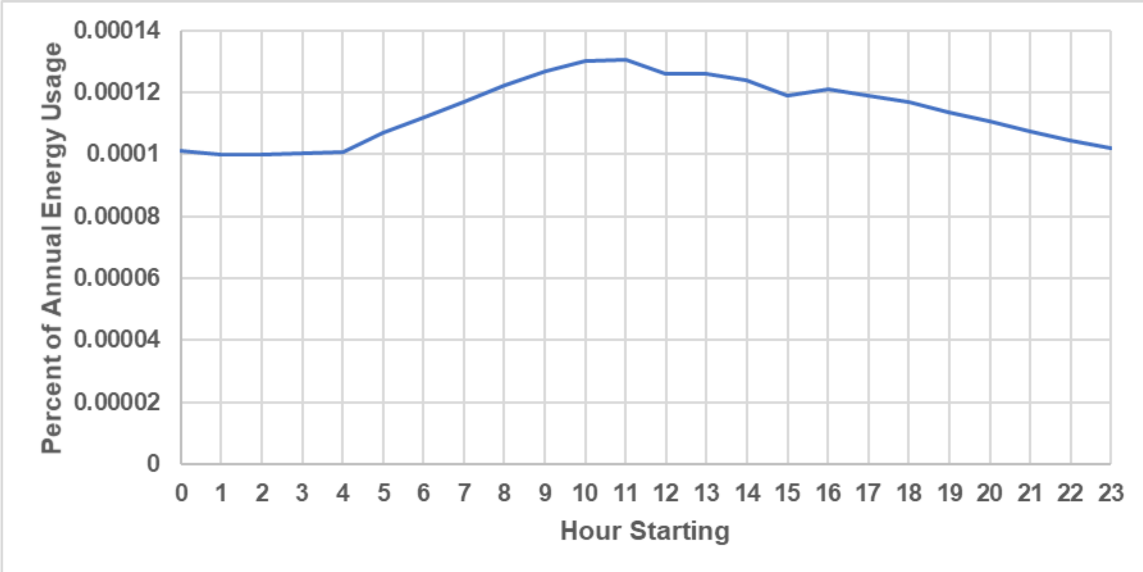
Example of an average 24-hour profile for all rate classes in an agricultural facility-type as taken from a single facility-type in a single forecast zone across the 2014, 2015, and 2016 base years.

Source: ADM Associates, Inc.

As seen in the plot, the load shapes for two of the general service rate classes (GS-1 and GS-2) bear a strong resemblance to one another. However, the profile for AG & PUMP shows atypical patterning in that it has unexpected jaggedness. Because this plot is an aggregated representation of the average daily load shape across the three-year period, the cause of these patterns can be attributed to multiple causes, such as changing of rate class for some meters over the year, or misattribution of sub-meters to a specific rate class. Because one cannot assume that these types of anomalies are attributable to data artifacts, ADM blended the profiles for each building sub-type across rate class. The result of blending the rate class level load data from Figure 187 as shown in

Figure 188: .

Figure 188: Example of Average 24-Hour Profile in an Agricultural Facility-Type Post-Aggregation



Example of an average 24-hour profile after aggregating across user groups in an agricultural facility-type in a single forecast zone across the 2014, 2015, and 2016 base years.

Source: ADM Associates, Inc.

As can be seen in Figure 188, aggregating the different rate classes together generates a load shape that reduces the anomalies attributable to any given rate class load shape. Although the example shown illustrates this process for data sets segmented by rate class, these patterns also exist in the data sets that were segmented by usage level. Therefore, all data segments per building facility-type per forecast zone were aggregated together.

Holidays

Holidays were derived from the list of federal standard holidays; however, the team excluded Columbus Day (Second Monday in October) and added Black Friday (the day after Thanksgiving) based on observations made in the AMI data.

Weather Data

An extract of weather data obtained was supplied by the Energy Commission for the years 2014 through 2016. Weather data consisted of outdoor air temperature, dew point, precipitation, windspeed, wind direction, total sky cover, and mean sea level pressure. Weather files were generated for all major AWS in California. The Energy Commission provided weighting files meant to define the appropriate weighting of each AWS to generate a forecast-zone-level weather file.

CHAPTER 5: Base Load Shapes: Industrial Sector

As with the agricultural sector, the Energy Commission's industrial load shapes are not currently generated at the end-use level. Rather, load shapes are currently isolated to the facility-type only. Energy demand in the industrial sector tends to be process-driven, i.e., the load shape for primary metals is primarily driven by the underlying fabrication of primary metals and thus most end-uses are also tied to that essential load shape. To reduce the overall number of load shapes, ADM mapped the 25 NAICS-based business types from the forecast model to 15 facility types represented as shown in Table 5. This mapping is accomplished with data preparation scripts that take the outputs of individual forecast models (bypassing the Summary Model) and develop inputs for HELM 2.0. The table can also be incorporated into the Summary Model to facilitate input to HELM 2.0.

Table 5 – Mapping of 25 NAICS-based industrial classifications to 15 building types.

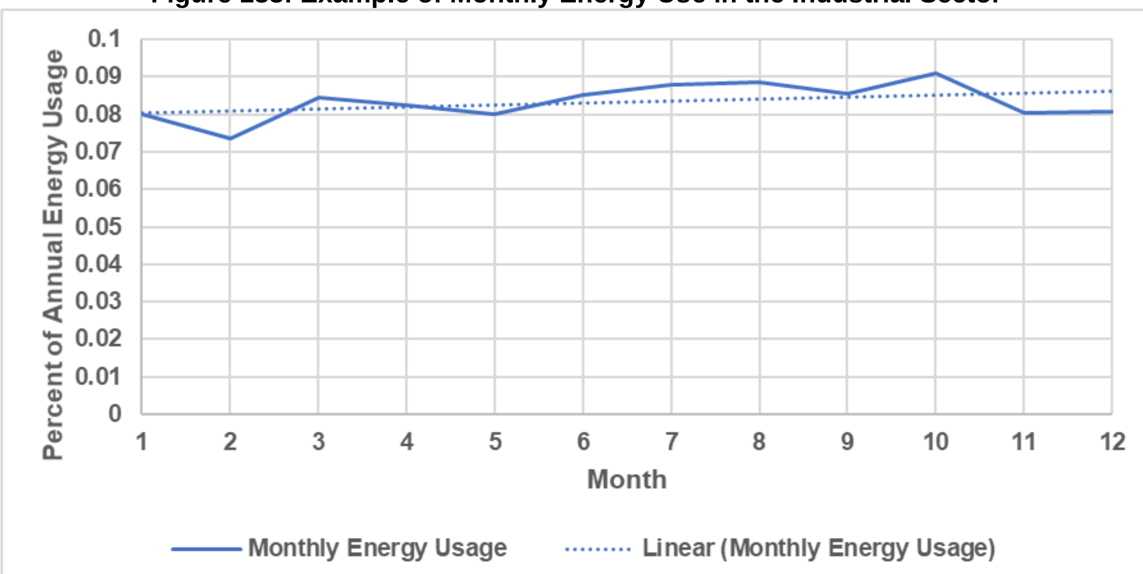
NAICS	ADM Building
311x, 312	Consumable Goods
3113, 3114	Consumable Goods
313	Textiles and Apparel
314	Textiles and Apparel
315, 316	Textiles and Apparel
1133, 321	Logging and Derivatives
322x	Logging and Derivatives
3221	Logging and Derivatives
323	Logging and Derivatives
324	Petroleum
325	Chemicals
326	Chemicals
327x	Construction Materials
3272	Construction Materials
3273	Construction Materials
331	Primary Metals
332	Fabricated Metal Products
333	Machinery
334x	Computers, Electronics
3344	Computers, Electronics
335	Lighting And Appliances
336	Transportation Equipment
337	Furniture
339	Nonelectrical durable goods
511	Publishing Industries

The primary goal for the industrial sector was to use the AMI data submitted by the three California IOUs to create a set of coefficients that accurately reflect the typical load shape for each facility type in each forecast zone and can be used to generate an 8,760-hour load shape for any given year. The remainder of this chapter will describe the method for generating said coefficients.

Regression Modeling

To generate sets of coefficients that represent every facility type for every forecast zone, the team relied on a regression-based algorithm based on a linear CDH regression model. Initial considerations were made to determine whether a simple compression of the data to a simple 12-month x 24-hour x 8-day matrix would be sufficient for modeling non-commercial/non-residential sectors. However, visual inspection of the monthly load shapes shows some variability over a calendar year which may have some collinearity with temperature. Figure 188 provides an example of a facility-type with energy use that fluctuates over a calendar year. Energy use increases during the months of June, July, and August, which suggests an increase in energy use that is collinear with a rise in temperature.

Figure 188: Example of Monthly Energy Use in the Industrial Sector



Example of monthly energy use in an industrial facility-type as taken from across an industrial facility-type in a single forecast zone in the 2015 base year.

Source: ADM Associates, Inc.

Because of the seasonal nature of energy use, ADM elected to include a temperature-based term in the regression equation. Although it is unlikely that the increase in energy use during the summer is tied specifically to HVAC, CDH can be used to approximate collinear variables, such as length of day, seasonal production, etc. ADM opted to use a CDH term rather than an hourly temperature value to mitigate potential sensitivity as temperature values reach extreme hot or extreme cold values. Using a CDH variable ensures that as the temperature dips towards negative values, the term associated with the weather variable cannot become negative.

ADM also noted significant load growth in the AMI data. As can be seen in Figure 188, there is a significant linear relationship between monthly energy usage and the number of months since the origin point (in this case, the origin being January of 2015). Therefore, ADM included a "day of year" term (with 1 representing January 1st) in the regression equation to include a term to capture the observed linear growth. Although ADM assumed that linear growth will continue to be present going forward, should someone want to exclude linear growth from a generated load shape, modeling the effect as part of the regression allows one to do so.

In addition to linear load growth and temperature-correlated factors, ADM also reviewed the impact of economic growth or decline on the resulting load shape. Because production in the industrial sector is explicitly tied to economic factors, ADM felt that changes in the economy could predict changes in the load shape for one year compared to another. Therefore, ADM included historical economic values as an independent variable in the model.

In addition to the main effects described above, ADM also expected the load to vary relative to weekday type (Sunday-Saturday and observed holidays) and hour of day. Furthermore, although scheduled loads should theoretically shift in accordance with daylight savings time, in real-world scenarios, some loads tend to shift relative to daylight savings time, while other loads end up remaining constant. Thus, ADM also considered whether an observation fell into the daylight savings time period an additional main effect for the models. Although the temporal main effects described in this paragraph could be modeled in a consolidated regression with appropriate interactive terms, ADM opted to segment the data set by the three temporal criteria (PDT/PST, weekday, and hour). This yields mathematically identical results while evades computational resource constraints.

After segmenting the data, each segment of data was then run through the following regression model:

$$y = \beta_0 + \beta_1 \cdot CDH + \beta_2 \cdot Day\ of\ Year + \beta_3 \cdot Economic\ Predictor + \varepsilon$$

Where:

- y is the predicted normalized load of the building
- β_0 is the intercept
- β_1 is the CDH weight
- β_2 is the linear growth term relative of the day of year (1-365 or 366)
- β_3 is the weight of the economic predictor
- ε is the error term

The above model was run for each data segment and the regression coefficients recorded for use in the base year load shape generator.

To select an appropriate CDH base term, the team iterated through five potential CDH base values (50 degrees Fahrenheit, 55 degrees Fahrenheit, 60 degrees Fahrenheit, 65 degrees Fahrenheit, and 70 degrees Fahrenheit) to determine which value provided the lowest amount of model error, as represented through NRMSE.[8]

Data Sources

The following section provides a list of the data sources used to generate ADM's industrial load shapes. In addition to listing the data source, a brief description of the data source and any data preparation activities are provided.

AMI Data

As part of this project, a data request was submitted to the three California IOUs requesting data for all non-residential sectors from the years 2014, 2015, and 2016. In response to this data request, the three IOUs provided averaged hourly data by building sub-type and either usage level (PG&E and SDG&E segmented data by high, medium, and low users) or rate class (SCE).

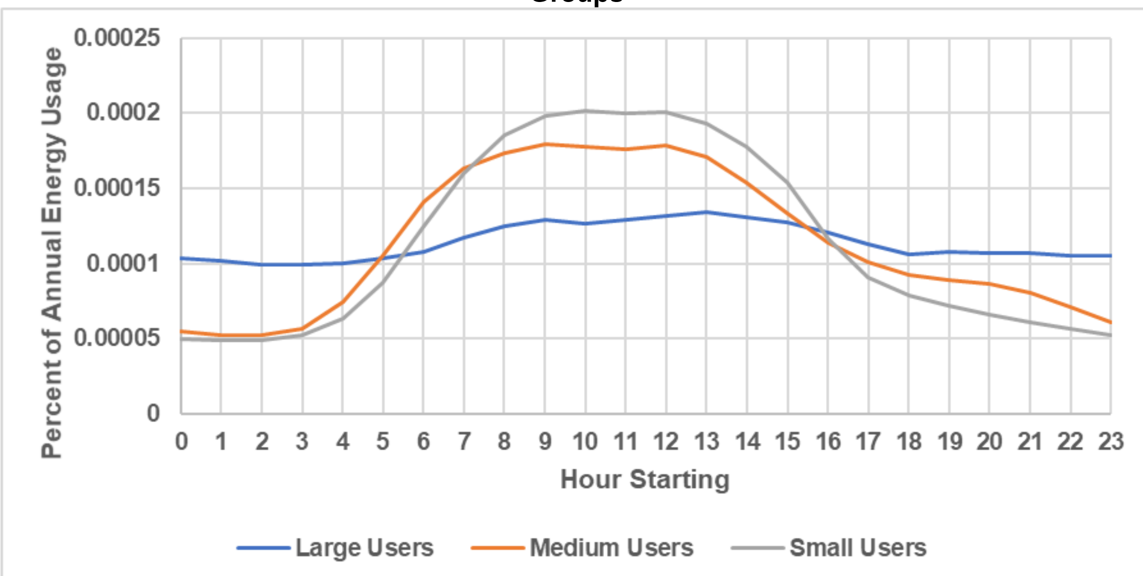
Prior to using the interval meter data, ADM first pre-treated all data. This pre-treatment consisted of standardizing the nomenclature of all files and merging the dataset with climate-zone specific hourly historical weather data obtained from the Energy Commission. Hourly timestamps were standardized to units of PST for the entire year (i.e., 11 p.m. PDT was standardized to 10 p.m. PST). Data was restricted to January 1, 2014 through December 31, 2016.

As part of the data validation process, ADM reviewed the data provided by the IOUs. ADM data for gaps and significant spikes within the data over the year. The plot in

Figure 189 depicts average daily load shapes obtained across all buildings of a given facility-type in a single forecast zone at different use levels.

8 The equation for calculating NRMSE is previously defined in the "Post Calibration Modeling" section of the Commercial chapter, beginning on page 118.

Figure 189: Example of Average 24-Hour Profiles for a Single Facility Type Across User Groups



Example of an average 24-hour profile for large, medium, and small users in an industrial facility-type as taken from all building types of a single facility-type in a single forecast zone across the 2014, 2015, and 2016 base years.

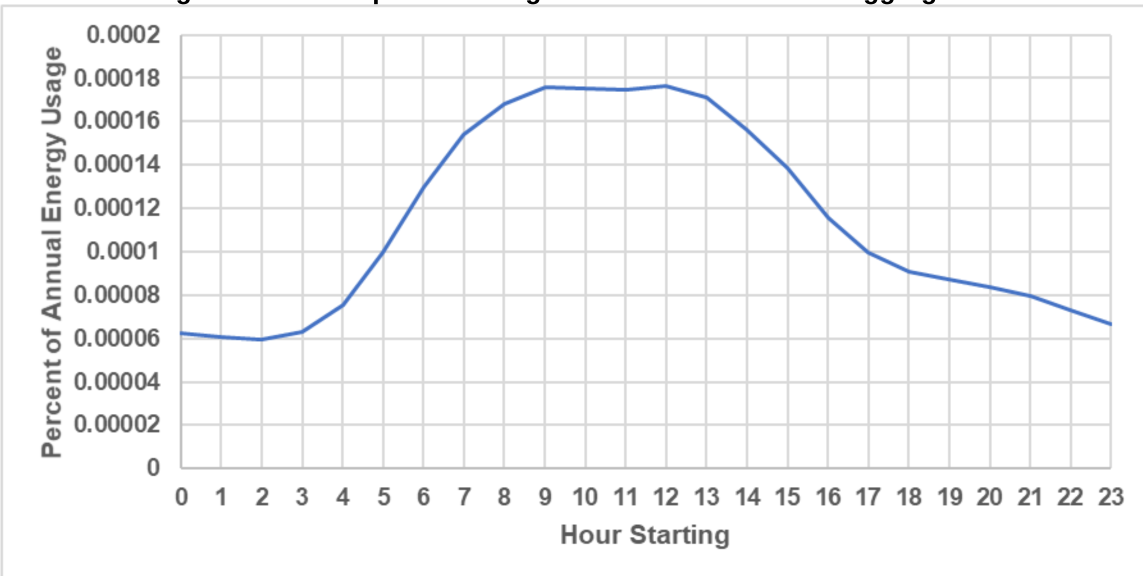
Source: ADM Associates, Inc.

In general, anomalies were not as pervasive in the data sets for the industrial sector as compared to the data sets obtained for the commercial or agricultural sector. However, for the purpose of maintaining consistency with the data preparation in other sectors, the team blended the profiles for each facility-type across rate class or usage level. The result of blending the rate class level load data from

Figure 189 as shown

Figure 190.

Figure 190: Example of Average 24-Hour Profiles Post-Aggregation



Example of an average 24-hour profile after aggregating across user groups in an industrial facility-type as taken from all building types of a single facility-type in a single forecast zone across the 2014, 2015, and 2016 base years.

Source: ADM Associates, Inc.

Economic Forecast Data

An extract of historical and forecasted economic data obtained from Moody's Analytics, Inc. was supplied by the Energy Commission for the years 2014 through 2028 at a quarterly resolution by NAICS category and forecast zone. The economic data provided for the industrial sector were GSP values in units of current-day millions of dollars.

Holidays

Holidays were derived from the list of federal standard holidays; however, ADM excluded Columbus Day (Second Monday in October) and added Black Friday (the day after Thanksgiving) based on observations made in the AMI data. Additionally, AMI data was reviewed for periods of low energy use to identify potential "holiday" periods. For each facility type in each forecast zone, the lowest 10% of days per year were identified. Dates that appeared consistent for more than 50% of all buildings were hallmarked as potential holidays and reviewed for consistency and clear pattern across the three base years prior to being designated as "holidays" in the industrial sector. The following dates were identified as additional Holidays:

- The first calendar week of December (which includes the first partial week of January)
- Easter Sunday
- Last two calendar weeks of December (which includes the last full week and last partial week of December)

Weather Data

An extract of weather data was supplied by the Energy Commission for the years 2014 through 2016. Weather data consisted of outdoor air temperature, dew point, precipitation, windspeed, wind direction, total sky cover, and mean sea level pressure. Weather files were generated for all major AWS in California. The Energy Commission provided weighting files meant to define the appropriate weighting of each AWS to generate a forecast-zone-level weather file.

CHAPTER 6: Base Load Shapes: Mining and Extraction

As with the agricultural and industrial sector, the Energy Commission's mining and extraction load shapes are not currently generated at the end-use level. Rather, load shapes are currently isolated to the facility-type only. Energy demand in the sector tends to be process-driven, i.e., the load shape for mining is primarily driven by mining and thus most end-uses are also tied to that essential load shape. There are three types represented in the mining and extraction sector:

- Mining (NAICS 212)
- Oil and gas extraction (NAICS 211, 213)
- Construction (NAICS 230)

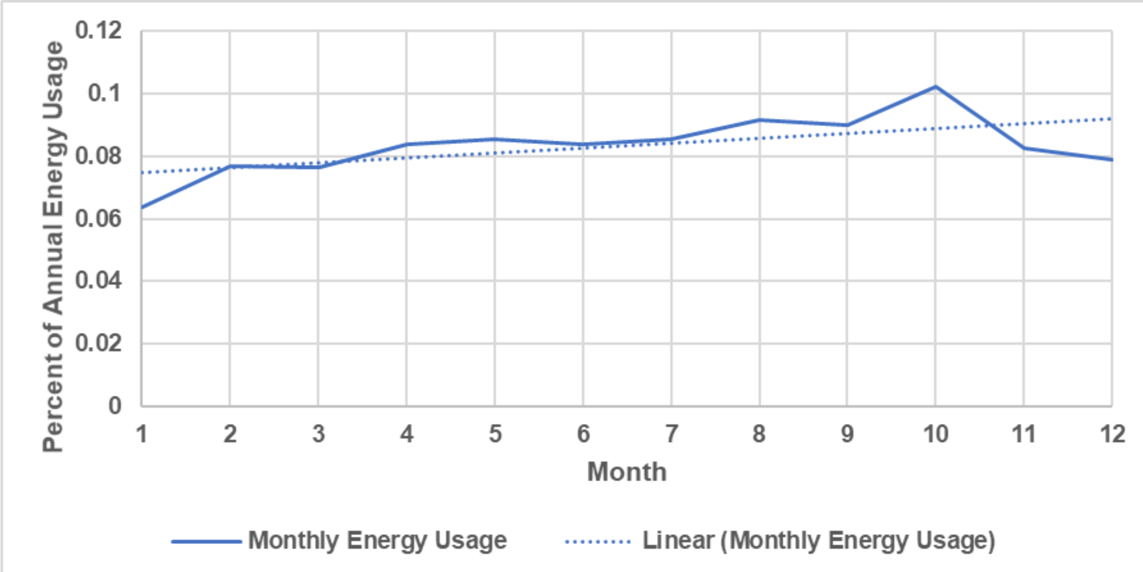
ADM's primary goal for the mining and extraction sector was to use the AMI data submitted by the three California IOUs to create a set of coefficients which accurately reflect the typical load shape for each facility type in each forecast zone and can be used to generate an 8,760-hour load shape for any given year. The remainder of this chapter will describe the methodology for generating said coefficients.

Regression Modeling

To generate sets of coefficients that represent every facility type for every forecast zone, the team relied on a regression-based algorithm based on a linear CDH regression model. Initial considerations were made to determine whether a simple compression of the data to a simple 12-month x 24-hour x 8-day matrix would be sufficient for modeling non-commercial/non-residential sectors. However, visual inspection of the monthly load shapes shows some variability over a calendar year.

Figure 191 illustrates this seasonality, with highest energy use during the summer months and lower energy use in the winter and shoulder seasons.

Figure 191: Example of Monthly Energy Usage for All Buildings of a Single Facility-Type in Mining and Extraction



Example of monthly energy usage in a mining and extraction facility-type in a single forecast zone in the 2015 base year.

Source: ADM Associates, Inc.

Because of the seasonal nature of energy use, ADM elected to include a temperature-based term in the regression equation. Although it is unlikely that the increase in energy usage during the summer is tied specifically to HVAC, CDH can be used to approximate collinear variables, such as length of day, seasonal production, etc. ADM opted to use a CDH term rather than an hourly temperature value to mitigate potential sensitivity as temperature values reach extreme hot or extreme cold values. Using a CDH variable ensures that as the temperature dips towards negative values, the term associated with the weather variable cannot become negative.

ADM also noted significant load growth in the AMI data. There is a significant linear relationship between monthly energy usage and the number of months since the origin point (in this case, the origin being January of 2015). Therefore, ADM included a "day of year" term (with 1 representing January 1st) in the regression equation to include a term to capture the observed linear growth. Although ADM assumed that linear growth will continue to be present going forward, should someone want to exclude linear growth from a generated load shape, modeling the effect as part of the regression allows one to do so.

In addition to linear load growth and temperature-correlated factors, ADM also reviewed the impact of economic growth or decline on the resulting load shape. Because production in the industrial sector is explicitly tied to economic factors, the researchers felt that changes in the economy could predict changes in the load shape for one year compared to another. Therefore, the researchers included historical economic values as an independent variable in the model.

In addition to the main effects described above, ADM also expected the load to vary relative to weekday type (Sunday-Saturday and observed holidays) and hour of day. Furthermore, although scheduled loads should theoretically shift in accordance with daylight savings time, in real-world scenarios, some loads tend to shift relative to daylight savings time, while other loads end up remaining constant. Thus, ADM also considered whether an observation fell into PST or PDT an additional main effect for the models. Although the temporal main effects described in this paragraph could be modeled in a consolidated regression with appropriate interactive terms, the researchers opted to segment the data set by the three temporal criteria (PDT/PST, weekday, and hour). This yields mathematically identical results while evades computational resource constraints.

After segmenting the data, each segment of data was then run through the following regression model:

$$y = \beta_0 + \beta_1 \cdot CDH + \beta_2 \cdot Day\ of\ Year + \beta_3 \cdot Economic\ Predictor + \varepsilon$$

Where:

- y is the predicted normalized load of the building
- β_0 is the intercept
- β_1 is the CDH weight
- β_2 is the linear growth term relative of the day of year (1-365 or 366)
- β_3 is the weight of the economic predictor
- ε is the error term

The above model was run for each data segment and the regression coefficients recorded for use in the base year load shape generator.

To select an appropriate CDH base term, ADM iterated through five potential CDH base values (50 degrees Fahrenheit, 55 degrees Fahrenheit, 60 degrees Fahrenheit, 65 degrees Fahrenheit, and 70 degrees Fahrenheit) to determine which value provided the lowest amount of model error, as represented through NRMSE.[9]

Data Sources

The following section provides a list of the data sources used to generate ADM's load shapes. In addition to listing the data source, a brief description of the data source and any data preparation activities are provided.

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9 The equation for calculating NRMSE is previously defined in the "Post Calibration Modeling" section of the Commercial chapter, beginning on page 118.

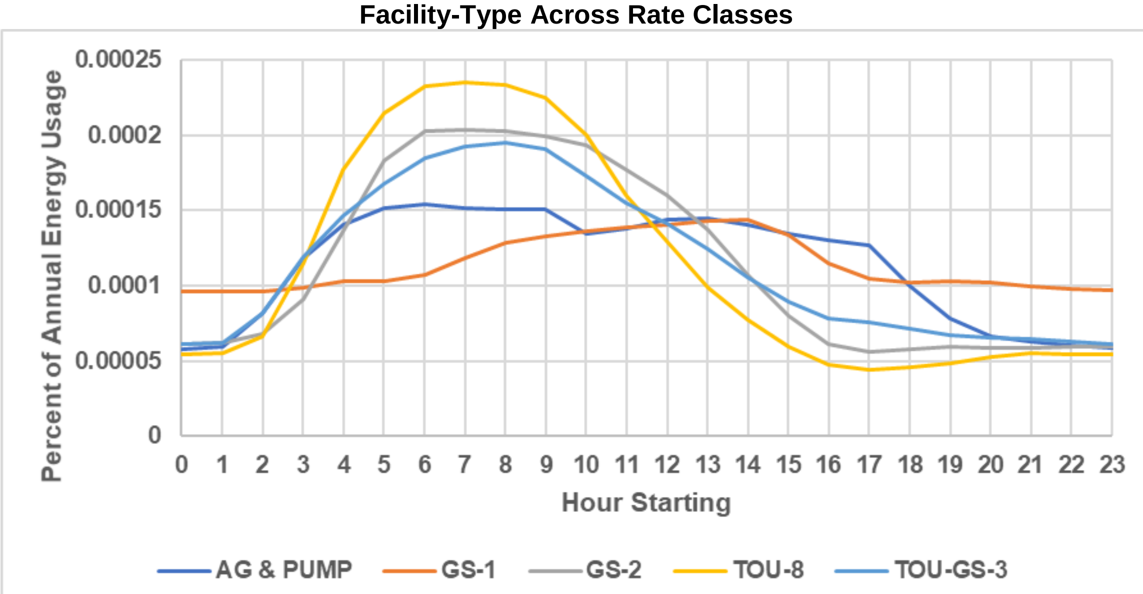
AMI Data

As part of this project, a data request was submitted to the three California IOUs requesting data for all non-residential sectors from the years 2014, 2015, and 2016. In response to this data request, the three IOUs provided averaged hourly data by building sub-type and either use level (PG&E and SDG&E segmented data by high, medium, and low users) or rate class (SCE).

Prior to using the interval meter data, the team first pre-treated all data. This pre-treatment consisted of standardizing the nomenclature of all files and merging the dataset with climate-zone specific hourly historical weather data obtained from the Energy Commission. Hourly timestamps were standardized to units of PST for the entire year (11 p.m. PDT was standardized to 10 p.m. PST). Data was restricted to January 1, 2014 through December 31, 2016.

As part of ADM's data validation process, ADM reviewed the data provided by the IOUs. ADM reviewed data for gaps and significant spikes within the data during the year. The plot in Figure 192 depicts average daily load shapes obtained for an average building in a single forecast zone of a single mining and Extraction facility-type.

Figure 192: Example of Average 24-Hour Profiles for a Single Mining and Extraction Facility-Type Across Rate Classes

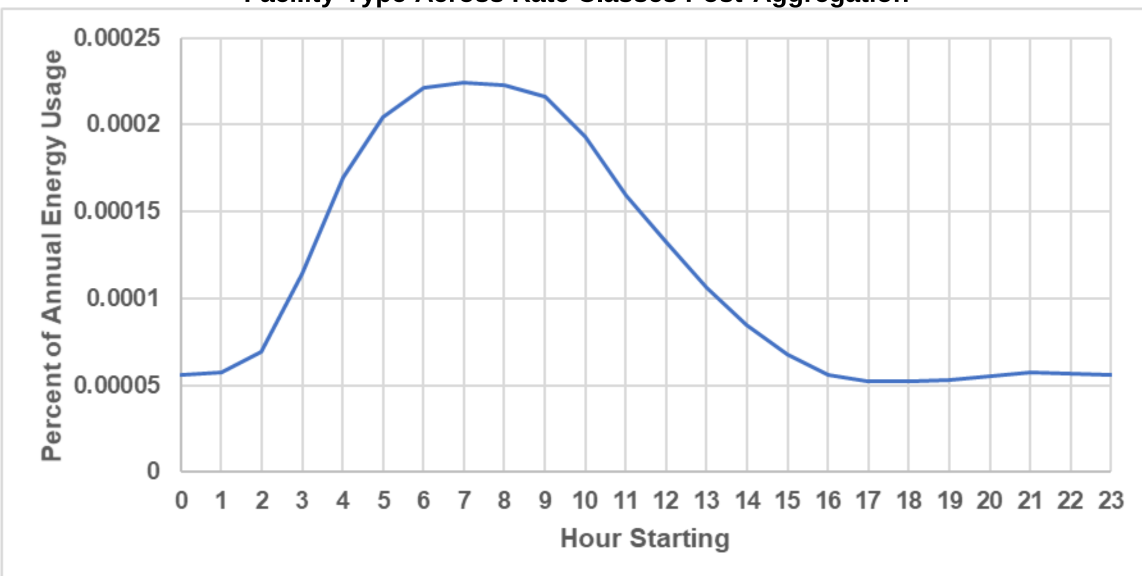


Example of an average 24-hour profile for different rate-classes as taken in a mining and extraction facility-type as taken from all building types of a single facility-type in a single forecast zone across the 2014, 2015, and 2016 base years.

Source: ADM Associates, Inc.

As seen in the plot, the load shapes are generally inconsistent with one another. Additionally, the profile for AG & PUMP shows unexpected jaggedness. Because this plot is an aggregated representation of the average daily load shape across the three-year period, the cause of this jaggedness may be attributed to anomalous drops at specific hours. The underlying cause of these patterns can be attributed to multiple causes, such as changing of rate class for some meters over the year, or misattribution of sub-meters to a specific rate class. Because one cannot assume that these types of anomalies are attributable to data artifacts, the researchers blended the profiles for each building sub-type across rate class. The result of blending the rate class level load data from Figure 192 as shown in Figure 193.

Figure 193: Example of Average 24-Hour Profiles for a Single Mining and Extraction Facility-Type Across Rate Classes Post-Aggregation



Example of an average 24-hour profile after aggregating across user groups in a mining and extraction facility-type as taken from all building types of a single facility-type in a single forecast zone across the 2014, 2015, and 2016 base years.

Source: ADM Associates, Inc.

As can be seen in Figure 193 aggregating the different rate classes together generates a load shape that reduces the anomalies attributable to any given rate class load shape. Although the example shown illustrates this process for data sets segmented by rate class, these patterns also exist in the data sets that were segmented by use level. Therefore, all data segments per building facility-type per forecast zone were aggregated together.

Economic Forecast Data

An extract of historical and forecasted economic data obtained from Moody's Analytics, Inc. was supplied by the Energy Commission for 2014-2028 at a quarterly resolution by NAICS category and forecast zone. The economic data provided for mining and oil and gas extraction were employment values in units of thousands of employees, while gross state product (GSP) values in units of current-day millions of dollars were provided for petroleum.

Holidays

Holidays were derived from the list of federal standard holidays; however, the team excluded Columbus Day (Second Monday in October) and added Black Friday (the day after Thanksgiving) based on observations made in the AMI data. Additionally, AMI data was reviewed for periods of low energy use to identify potential “holiday” periods. For each facility type in each forecast zone, the lowest 10% of days per year were identified. Dates that appeared consistent for more than 50% of all buildings were hallmarked as potential holidays and reviewed for consistency and clear pattern across the three base years prior to being designated as “holidays” in the mining and extraction sector. The following dates were identified as additional holidays:

- Christmas Eve
- New Year’s Eve

Weather Data

An extract of weather data obtained from was supplied by the Energy Commission for the years 2014 through 2016. Weather data consisted of outdoor air temperature, dew point, precipitation, windspeed, wind direction, total sky cover, and mean sea level pressure. Weather files were generated for all major AWS in California. The Energy Commission provided weighting files meant to define the appropriate weighting of each AWS to generate a forecast-zone-level weather file.

CHAPTER 7: Base Load Shapes: TCU Load Shapes

As with the other non-residential and non-commercial sectors, the Energy Commission's TCU sector load shapes are not currently generated at the end-use level. Rather, load shapes are currently isolated to the facility-type only. Energy demand in the TCU sector tends to be process-driven, specifically the load shape for wireless telecommunications is primarily driven by wireless telecommunications and thus most end-uses are also tied to that essential load shape. There are 13 facility-types in the TCU sector:

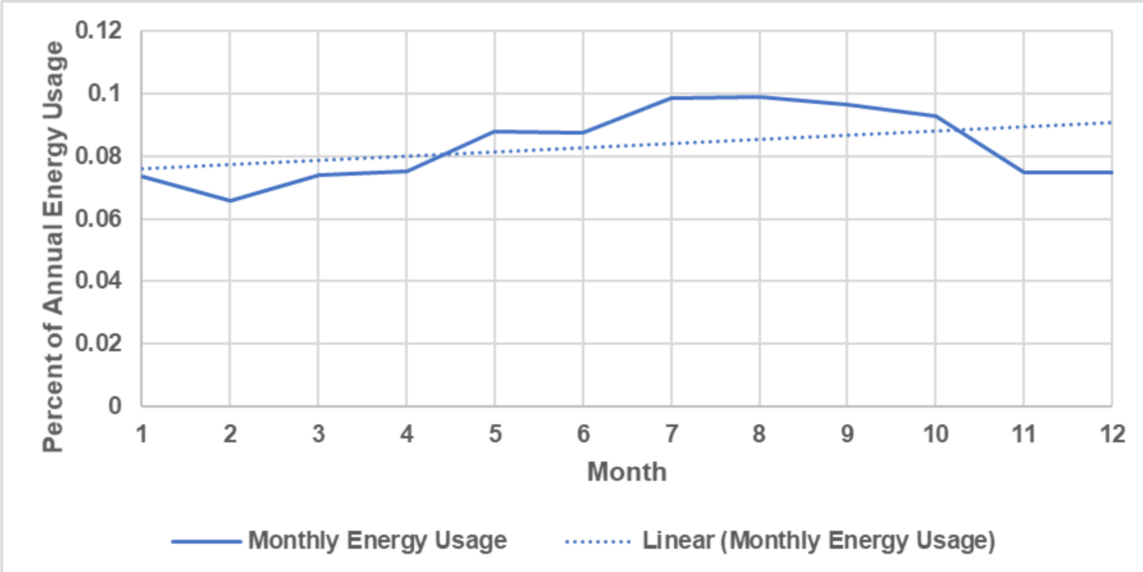
- Air transportation,
- Broadcasting,
- Ground transportation,
- Motor freight,
- National security,
- Pipelines,
- Postal service,
- Railroad transportation,
- Rental and leasing services,
- Utilities,
- Waste management,
- Water transportation and sightseeing,
- Wireless telecommunication.

ADM's primary goal for the TCU sector was to use the AMI data submitted by the three California IOUs to create a set of coefficients which accurately reflect the typical load shape for each facility type in each forecast zone and can be used to generate an 8,760-hour load shape for any given year. The remainder of this chapter will describe the methodology for generating said coefficients.

Regression Modeling

To generate sets of coefficients that represent every facility type for every forecast zone, the researchers relied on a regression-based algorithm based on a linear CDH regression model. Initial considerations were made to determine whether a simple compression of the data to a simple 12-month x 24-hour x 8-day matrix would be sufficient for modeling non-commercial/non-residential sectors. However, visual inspection of the monthly load shapes shows some variability over a calendar year. Figure 194 illustrates this seasonality, with highest energy use during the summer months and lower energy use in the winter and shoulder seasons.

Figure 194: Example of Monthly Energy Usage for All Buildings of a Single Facility-Type in TCU



Example of monthly energy usage in a TCU facility-type in a single forecast zone in the 2014 base year.

Source: ADM Associates, Inc.

Because of the seasonal nature of energy use, ADM elected to include a temperature-based term in the regression equation. Although it is unlikely that the increase in energy usage during the summer is tied specifically to HVAC, CDH can be used to approximate collinear variables, such as length of day, seasonal production, etc. ADM opted to use a CDH term rather than an hourly temperature value to mitigate potential sensitivity as temperature values reach extreme hot or extreme cold values. Using a CDH variable ensures that as the temperature dips towards negative values, the term associated with the weather variable cannot become negative.

ADM also noted significant load growth in the AMI data. As can be seen in Figure 194, there is a significant linear relationship between monthly energy usage and the number of months since the origin point (in this case, the origin being January of 2016). Therefore, the researchers included a "day of year" term (with 1 representing January 1st) in the regression equation to include a term to capture the observed linear growth. Although ADM assumed that linear growth will continue to be present going forward, should someone want to exclude linear growth from a generated load shape, modeling the effect as part of the regression allows one to do so.

In addition to linear load growth and temperature-correlated factors, ADM also reviewed the impact of economic growth or decline on the resulting load shape. Because changes in the TCU sector is explicitly tied to economic factors, ADM felt that changes in the economy could predict changes in the load shape for one year compared to another. Therefore, ADM included historical economic values as an independent variable in the model.

In addition to the main effects described above, ADM also expected the load to vary relative to weekday type (Sunday-Saturday and observed holidays) and hour of day. Furthermore, although scheduled loads should theoretically shift in accordance with daylight savings time, in real-world scenarios, some loads tend to shift relative to daylight savings time, while other loads end up remaining constant. Thus, the team also considered whether an observation fell into PDT or PST an additional main effect for the models. Although the temporal main effects described in this paragraph could be modeled in a consolidated regression with appropriate interactive terms, ADM opted to segment the data set by the three temporal criteria (PDT/PST, weekday, and hour). This yields mathematically identical results while evades computational resource constraints.

After segmenting the data, each segment of data was then run through the following regression model:

$$y = \beta_0 + \beta_1 \cdot CDH + \beta_2 \cdot Day\ of\ Year + \beta_3 \cdot Economic\ Predictor + \varepsilon$$

Where:

- y is the predicted normalized load of the building
- β_0 is the intercept
- β_1 is the CDH weight
- β_2 is the linear growth term relative of the day of year (1-365 or 366)
- β_3 is the weight of the economic predictor
- ε is the error term

The above model was run for each data segment and the regression coefficients recorded for use in the base year load shape generator.

To select an appropriate CDH base term, the researchers iterated through five potential CDH base values (50 degrees Fahrenheit, 55 degrees Fahrenheit, 60 degrees Fahrenheit, 65 degrees Fahrenheit, and 70 degrees Fahrenheit) to determine which value provided the lowest amount of model error, as represented through NRMSE.[10]

Data Sources

The following section provides a list of the data sources used to generate TCU load shapes. In addition to listing the data source, a brief description of the data source and any data preparation activities are provided.

AMI Data

As part of this project, a data request was submitted to the three California IOUs requesting data for all non-residential sectors from the years 2014, 2015, and 2016. In response to this data request, the three IOUs provided averaged hourly data by building

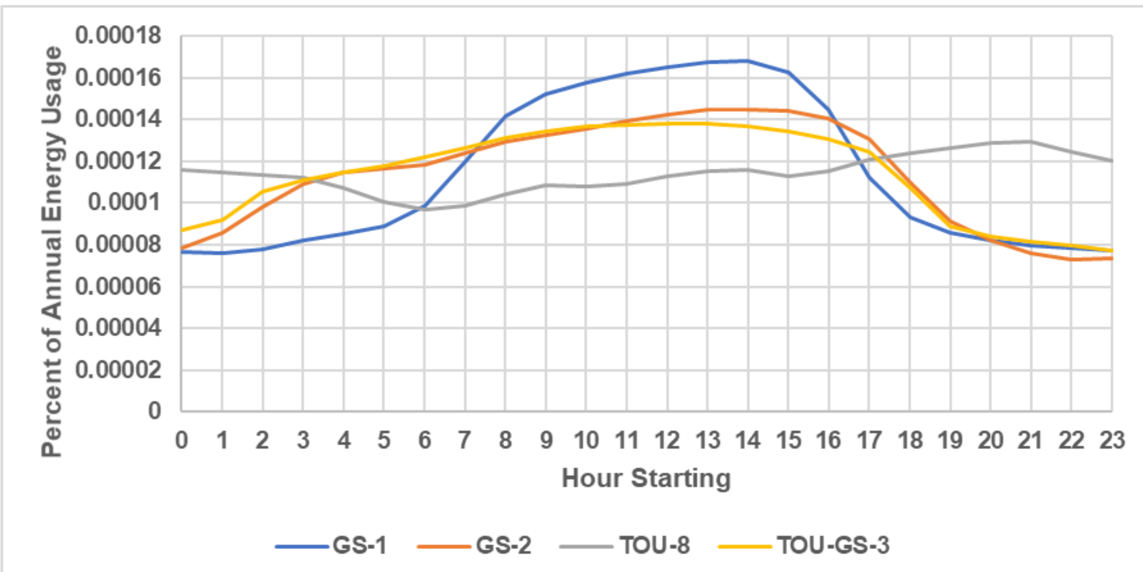
10 The equation for calculating NRMSE is previously defined in the "Post Calibration Modeling" section of the Commercial chapter, beginning on page 118.

sub-type and either usage level (PG&E and SDG&E segmented data by high, medium, and low users) or rate class (SCE).

Prior to using the interval meter data, ADM first pre-treated all data. This pre-treatment consisted of standardizing the nomenclature of all files and merging the dataset with climate-zone specific hourly historical weather data obtained from the Energy Commission. Hourly timestamps were standardized to units of PST for the entire year (i.e., 11 p.m. PDT was standardized to 10 p.m. PST). Data was restricted to the period of January 1, 2014 through December 31, 2016.

As part of the data validation process, the team reviewed the data provided by the IOUs. ADM reviewed data for gaps and significant spikes within the data over the year. The plot in Figure 195 depicts average daily load shapes obtained for a TCU facility-type in a single forecast zone.

Figure 195: Example of Average 24-Hour Profiles for a Single TCU Facility-Type Across Rate Classes



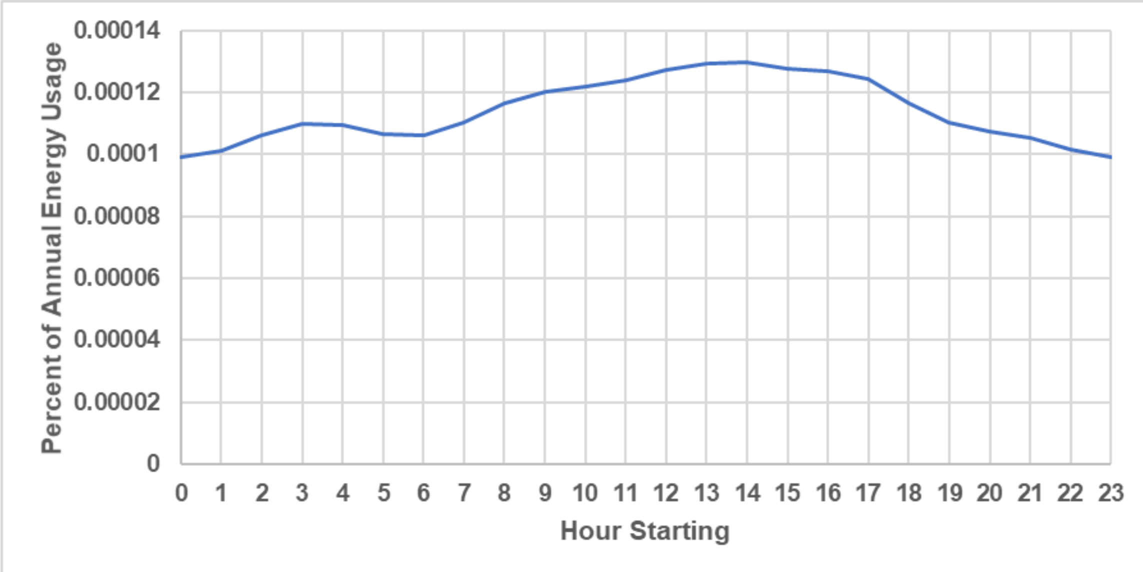
Example of an average 24-hour profile for different rate-classes as taken in a TCU facility-type as taken from all building types of a single facility-type in a single forecast zone across the 2014, 2015, and 2016 base years.

Source: ADM Associates, Inc.

As seen in the plot, the load shapes are generally inconsistent with one another, although anomalies were not as pervasive in the data sets for the TCU sector as compared to the data sets obtained for the commercial or agricultural sector. However, to maintain consistency with the data preparation in other sectors, ADM blended the profiles for each facility-type across rate class or usage level. The result of blending the rate class level load data from Figure 195 as shown in

Figure 196.

Figure 196: Example of Average 24-Hour Profiles for a Single TCU Facility-Type Across Rate Classes Post-Aggregation



Example of an average 24-hour profile after aggregating across user groups in a TCU facility-type as taken from all building types of a single facility-type in a single forecast zone across the 2014, 2015, and 2016 base years.

Source: ADM Associates, Inc.

Economic Forecast Data

An extract of historical and forecasted economic data obtained from Moody's Analytics, Inc. was supplied by the Energy Commission for 2014-2028 at an annual resolution by NAICS category and IOU. The economic data provided for Air Transportation, Broadcasting, National Security, Pipelines, and Utilities were employment values in units of thousands of employees, while total population in units of thousands.

Holidays

Holidays were derived from the list of federal standard holidays; however, the team excluded Columbus Day (Second Monday in October) and added Black Friday (the day after Thanksgiving) based on observations made in the AMI data.

Weather Data

An extract of weather data obtained was supplied by the Energy Commission for the years 2014 through 2016. Weather data consisted of outdoor air temperature, dew point, precipitation, windspeed, wind direction, total sky cover, and mean sea level pressure. Weather files were generated for all major AWS in California. The Energy Commission provided weighting files meant to define the appropriate weighting of each AWS to generate a forecast-zone-level weather file.

CHAPTER 8: Base Load Shapes: Streetlighting

As with the other non-residential and non-commercial sectors, the Energy Commission's streetlighting sector load shapes are not currently generated at the end-use level. Rather, load shapes are currently isolated to holistic "streetlighting" load shapes for each forecast zone. Unlike the other sectors, streetlighting, which refers primarily to outdoor lighting fixtures such as street lamps, and traffic signals, remain largely unmetered as their energy usage is governed by rate tariffs.

Interval meter data provided by the three California IOUs showed reduced, yet significant usage during daytime, indicating that the metered data available to utilities are comprised of area lighting as well as lights that are always on, such as traffic lights. ADM decided to develop an overall streetlighting shape as a mix of two general components: photocell-controlled streetlighting and always-on traffic signals.

Photocell Load Shape

ADM generated a load shape that is consistent with lights controlled by photocells or astronomical time clocks. One load shape suffices to be representative at the statewide level, as the key characteristic is that the lights are off from dawn to dusk. Sunrise and sunset times are readily available on various online websites. ADM found the Astronomical Data Portal from the United Kingdom Hydrographic Office (2012) to be particularly useful, and selected Merced, California for its central location and converted the sundown and sunrise times to lamp run-times. To simulate the effects of photocells or astronomical time clocks, ADM turned photocells on 15 minutes after sunrise, and 15 minutes before sunset, resulting in 4,152 hours of operation per year.

Traffic Lights

Traffic lights tend to have "flat" load shapes. For example, either the red, yellow, or green traffic light is on at any given time.

Weighting to Represent Nonmetered Streetlighting

Based on dimensionality arguments, one would expect streetlighting energy usage to be orders of magnitude larger than traffic lighting energy usage. To estimate the total weight of traffic lights, ADM used a survey of street and traffic lighting published by the League of Oregon Cities (LOC 2010, 13-40). The report lists the number of traffic lights and street lights in dozens of towns and cities in Oregon. Interestingly, traffic lighting and street lighting tend to be well represented by linear functions of overall population, over large population range. On average, traffic lights account for 0.26% of the overall street and traffic lighting energy use.

CHAPTER 9: PV Load Shapes

Method

ADM's approach to modeling PV load shapes included sensitivity studies, data gathering, performance simulation, and time-averaging of results.

SAM Modeling and Sensitivity Studies

ADM started by inspecting load shapes from several typical residential PV systems and configurations. By comparing results from numerous simulations, ADM quickly determined that the particular make and model, or even inverter type had negligible effects on the generation load shapes. The most significant factors were location, orientation, tilt, and shading of the panels. Shading, however, was only influential in extreme cases—any amount shading that would qualify for rebates from the CSI did not result in significant variation of overall output or load shapes. Given the relative importance of geographical location and orientation, ADM decided to create, for each forecast zone, four separate load shapes corresponding to panels oriented in the four cardinal directions. Panel tilt had minor impacts on load shapes, and ADM selected market-average tilts of 22° for residential installations and 14° for commercial installations. Although data do not exist to characterize "market average" shading percentages, ADM applied reasonable estimates based on inspection of satellite photographs of solar panel installations, and by referencing the CSI eligibility requirements with respect to shading.

Data Sources

The SAM includes libraries of data required for performance simulation, including weather data and PV system specifics. To characterize market average installation tilts and fractions of installations in various orientations, ADM used the "Currently Interconnected Data Set" from the California Distributed Generation Statistics[11] website. The data set includes system and installation specifics from thousands of extant systems.

Time Averaging of PV Output

The SAM can simulate PV generation under various weather conditions. In building energy simulations, it is customary to use Typical Meteorological Year (TMY) weather files, which contain actual historic weather data, including heat waves, cold snaps, and

11 Energy Solutions, 2016. *California Distributed Generation Statistics.* California Public Utilities Commission. https://www.californiadgstats.ca.gov/.

other weather events. Average weather, as opposed to typical weather, would lead to underestimations of peak cooling and heating loads. Application of TMY data might have unintended consequences, however, in simulations of solar power output. It is not guaranteed that PV generation and electric demand are synchronized or strongly correlated. Heat waves occur for complex reasons, which may not be predictably correlated to PV generation output. For this reason, it is desirable to think of solar generation in terms of expectation values for given days and hours of the year. For example, forecasters may want to know, what fraction of the total annual PV generation output is likely to occur on August 28. Data from any one year may have August 28 as a particularly cloudy or sunny day, but an average over several years will approximate the likelihood that August 28 is cloudy. ADM simulated generation using actual weather data from 2012-2017, as weather data was available for these years at the resolution needed to run the SAM. All six sets of runs were averaged to create the PV generation profiles for each forecast zone and sector.

CHAPTER 10:
EV Charging Load Shapes

Methodology

ADM recognized early on that EV charging load shapes are of increasing importance as the transportation market embarks on historic changes with respect to fuel diversity, and particularly with electric demand. One challenge associated with forecasting the time-variable aspect of electric demand in the transportation sector is that most of the electric demand is yet to come. ADM's approach was to collect contemporary data on vehicle charging patterns, while modeling dynamic price response as more customers switch to grid-integrated rates in the future.

Data Sources

The project team attempted to obtain recent and representative data on charging load shapes.

- Vehicle charging session data from ChargePoint
- Individually metered residential charging profiles from the Joint IOU Electric Vehicle Load Research Report
- Trending data from bus and shuttle fleets
- Energy Commission Staff Report - California Plug-In Electric Vehicle Infrastructure Projections 2017-2025
- Light-Duty Plug-in Electric Vehicle Energy and Emission Calculator from the 2017 IEPR[12]
- Forecast scenarios related to time of use rates offered by IOUs
- Conversations with the Energy Commission Transportation Energy Forecasting Unit staff regarding forecast process for light duty, medium duty, and heavy-duty vehicles

Single Family Residential Charging Data

ADM obtained a random sample of charging session data from ChargePoint. ChargePoint is the world's largest network of EV charging stations, and also provides chargers for residential use, in single family and multifamily settings. ADM ordered charging session data from the calendar year 2017 for 500 single family residential accounts, and 2,000 commercial accounts – 95 of which were installed in multifamily apartment complexes. The data were anonymized but included important data fields

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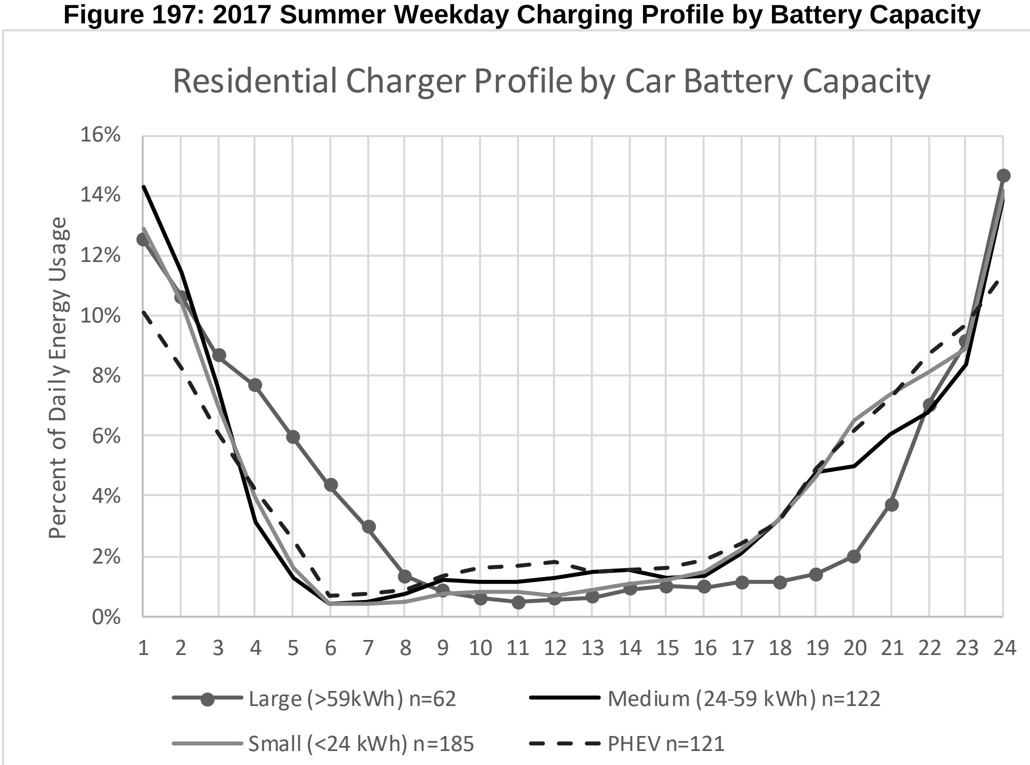
12 (Yowell, 2018) https://www.energy.ca.gov/sb350/IRPs/documents/Light_Duty_Plug-In_EV_Energ_and_Emission_Calculator.xlsx

such as charging session start and end times, total charging energy in kilowatt hours (kWh), charger maximum capacity, car make and model, battery capacity, and zip code of charger installation location.

The single family charging data included vehicle make and model, as well as battery capacity. Given that the typical battery capacity is expected to continue to increase over the next decade, the team reviewed charging profiles by battery capacity. Figure 197 below shows the typical daily charging profile for cars of various battery capacities. In the 2017 ChargePoint data, only 62 vehicles had battery capacities of 59 kWh or greater, and 56 of them were Chevrolet Bolts. Large-battery vehicles tend to start and finish charging significantly later than other vehicles, which are basically indistinguishable from each other. ADM has confirmed with ChargePoint that the difference in start time is not due to a systematic data issue such as one make/model (necessarily, the Bolts) being reported on Eastern Time rather than Pacific Time. The most likely cause for the late charging start is that the larger-battery vehicles are typically newer and have advanced charging menus that enable customers to enter utility rate schedules to ensure charging starts during off-peak periods.

Figure 197: 2017 Summer Weekday Charging Profile by Battery Capacity

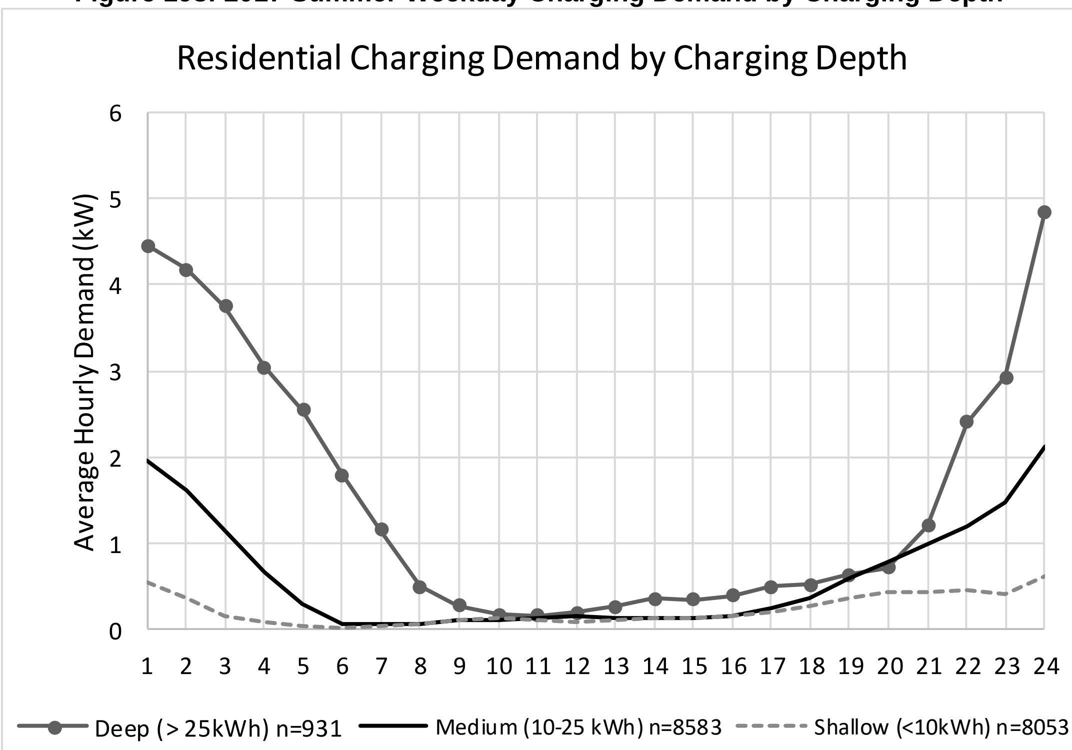


Typical hourly load shapes in summer weekdays for plug-in hybrid vehicles (dashed profile), and battery electric vehicles with small battery capacities (light grey profile), medium battery capacities, (solid dark grey profile), and large battery capacities (solid profile with markers). The late charging start for the larger capacity vehicles is likely due to the fact that the larger battery vehicles are late-model cars with advanced charging menus.

Source: ADM Associates, Inc, data from ChargePoint

Most of the chargers were level two chargers with maximum charging capacities between 6 kW and 8 kW. Therefore, the total and peak energy demand for a given charging session was strongly determined by the charging depth, defined here as the total energy transferred during a charging session. Figure 198 shows hourly charging demands on summer weekdays for charging sessions of various depths. Deep charges corresponded, on average, to 37 kWh of energy usage per day. Medium charges averaged 15 kWh. Shallow charges averaged 6 kWh. Most of the excess energy demand for deep charges, however, occurs during off-peak periods.

Figure 198: 2017 Summer Weekday Charging Demand by Charging Depth



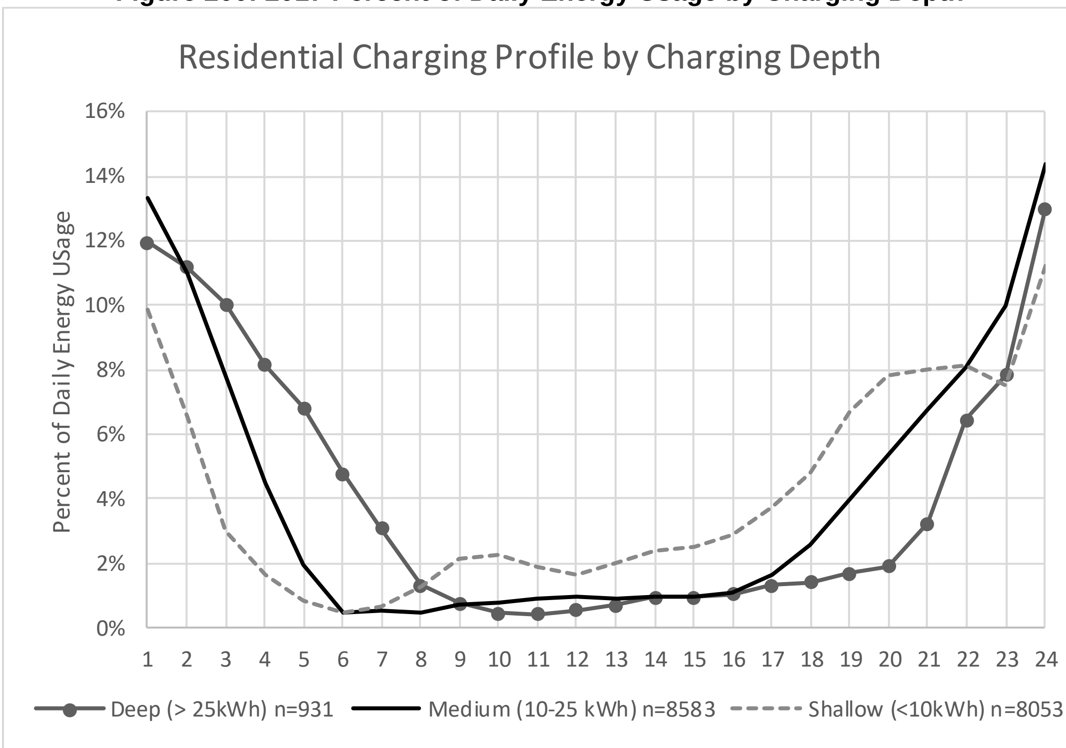
Typical hourly electric demand in summer weekdays for shallow charges (dashed profile), medium charges (dark solid profile) and deep charges (solid profile with markers).

Source: ADM Associates, Inc, data from ChargePoint

The data in Figure 198 can be deceiving because they portray demands associated with individual charging sessions. Deep charges require more energy but are likely to be less frequent, given a fixed overall charging demand in a given geographical area. The grid experiences the diversified impact of charging, rather than individual loads. To gain the grid's perspective, the data in Figure 198 are normalized to percentage of daily energy usage by hour. Results are shown in

Figure .

Figure 200: 2017 Percent of Daily Energy Usage by Charging Depth



Typical hourly load shapes in summer weekdays for shallow charges (dashed profile, less than 10 kWh delivered), medium charges (dark solid profile, between 10 kWh and 25 kWh delivered) and deep charges (solid profile with markers, more than 25 kWh delivered).

Source: ADM Associates, Inc, data from ChargePoint

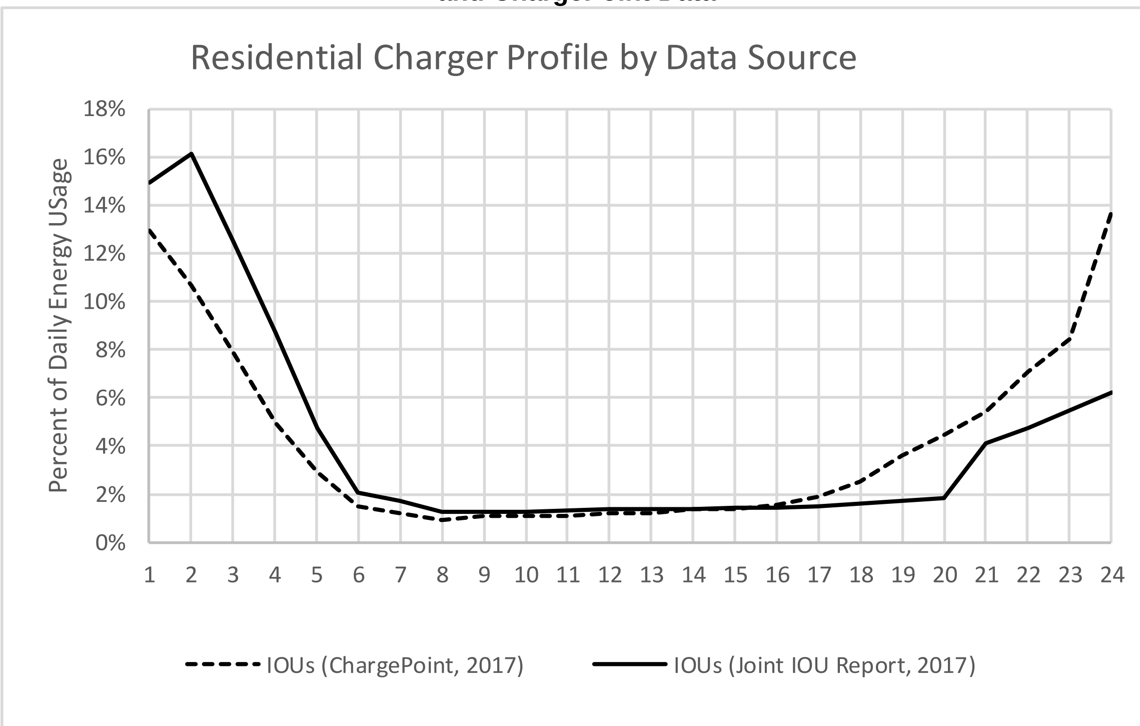
Deep charges actually have the least peak demand contribution (loosely defined as 2 PM to 8 PM) of all charge types. As of this writing, ADM hypothesizes that the distinct profile associated with deep charges is strongly correlated with vehicle vintage; specifically, with the user-friendly features that allow casual users to schedule charging during off-peak times.

Comparison of ChargePoint Data to Individually Metered IOU Data

Pacific Gas and Electric, SCE, and SDG&E publish the Joint IOU Electric Vehicle Load Research Report on an annual basis. The 2017 report included load shapes from individually metered chargers from residential customers that are on special time of use (TOU) rates for customers with electric vehicles. ADM transcribed these load shapes into a spreadsheet and compared the weekday charging profile to the data from ChargePoint. The comparison is shown in Figure 199. The profiles are quite similar, but the

ChargePoint data tends to show demand growth at 4 PM, whereas the IOU data shows suppressed demand until 8 PM. The likely cause of this difference is that 100% of IOU customers are on TOU rates, whereas a much smaller fraction of the ChargePoint customers are on TOU rates. Although the utility rates are not known for the ChargePoint customers, ADM estimates that 24% of electric IOU customers that were electric vehicle owners, were on TOU rates in 2017[13].

Figure 199: 2017 Comparison of Charging Profiles Developed from the Joint IOU Report and ChargePoint Data



Typical hourly load shapes in summer weekdays for single family homes as from the Joint IOU report (solid profile, averaged over all utilities) and ChargePoint (dashed profile). Note that 100% of customers in the Joint IOU data set are on time of use rates, whereas the authors estimate that only fewer than 50% of ChargePoint customers were likely to be on time of use rates in 2017.

Source: ADM Associates, Inc, data from PG&E, SCE, SDG&E, and ChargePoint

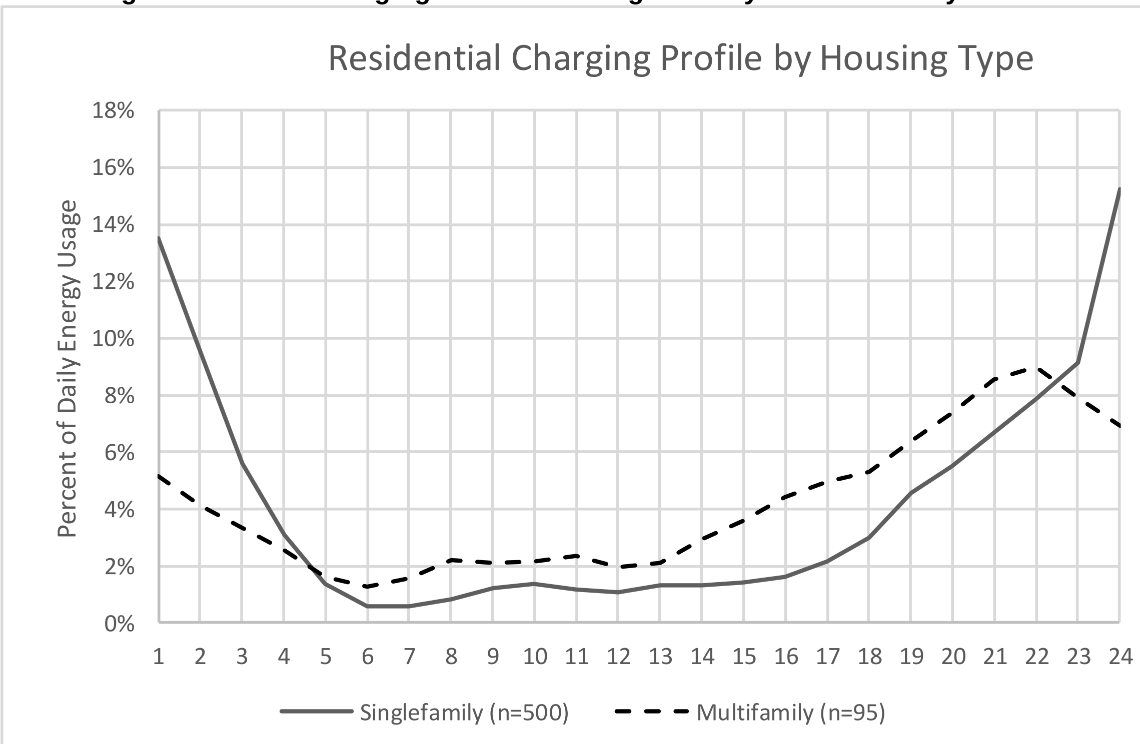
Multifamily Residential Charging Data

The ChargePoint data also included session data for 95 chargers in multifamily apartments. The multifamily data appear to be less concentrated in the off-peak periods, as shown in Figure 200. ADM does not have additional data to explain the difference in load shapes, but ADM has excluded the possibility that the type or vintage of electric vehicles are significantly different between the two housing types. One

13 This quantity is derived in the subsequent section regarding price elasticity.

possible explanation is that some of the multifamily chargers may be on commercial accounts associated with property management rather than individual tenants, and as a result the price response may be less acute.

Figure 200: 2017 Charging Profiles for Single Family and Multifamily Homes



Typical hourly load shapes in summer weekdays for single family homes (solid profile) and multifamily homes (dashed profile).

Source: ADM Associates, Inc, data from ChargePoint

Nonresidential Light Duty Vehicle Charging Data

ADM obtained a random sample of non-residential charging session data from ChargePoint. The data were anonymized, but included a specification of the business type associated with the charging station. Although all chargers are installed in the commercial establishments, ADM attempted to categorize the charging locations into those that are most likely to be associated with one of three classes: personal vehicles, commercial fleet vehicles, or government fleet vehicles. The classification is made to align with forecast data from the Energy Commission's transportation energy forecasting unit.

The forecast includes total energy usage associated with personal light duty EV, yet these vehicles can be charged either at residential properties or commercial properties. Charging of personal vehicles at commercial properties is sometimes referred to as "destination charging." Some examples of destination charging include charging at the workplace and charging while parked in a parking lot or parking garage. Table 6 shows the classification developed by ADM. As an example, it is assumed that most charging in high schools or casinos are charging of personal vehicles of staff or patrons, while categories that include the word "fleet" are associated with commercial or government fleet vehicles, rather than personal vehicles.

Table 6: Assignment of Vehicle Ownership Type Classifications to Commercial Categories Provided by ChargePoint

Category	Subcategory	Classification	Count
Demo Unit	Na	Commercial Vehicle	1
Fleet	Depot	Commercial Vehicle	6
Fleet	Distributed	Commercial Vehicle	36
Healthcare	Hospital / Treatment Center	Commercial Vehicle	35
Healthcare	Small Medical	Commercial Vehicle	9
Hospitality	Parks and Recreation (Private)	Commercial Vehicle	2
Retail	Auto Dealership	Commercial Vehicle	39
Workplace	Fleet	Commercial Vehicle	5
Workplace	Na	Commercial Vehicle	3
Education	High School / Other	Personal Vehicle	15
Education	University / College	Personal Vehicle	83
Government	Civilian Workplace	Personal Vehicle	24
Hospitality	Amusement Park	Personal Vehicle	2
Hospitality	Casino	Personal Vehicle	13
Hospitality	Hotel / Resort	Personal Vehicle	21
Hospitality	Large	Personal Vehicle	2
Hospitality	Restaurant	Personal Vehicle	1
Hospitality	Stadium / Entertainment Venue	Personal Vehicle	4
Hospitality	Winery / Brewery	Personal Vehicle	1
Municipal	Library	Personal Vehicle	8
Municipal	Municipal Parking	Personal Vehicle	96
Municipal	Municipal Workplace	Personal Vehicle	29
Parking	Airport	Personal Vehicle	18
Parking	Commercial	Personal Vehicle	68
Parking	Mass Transit	Personal Vehicle	6
Retail	Big Box / Superstore	Personal Vehicle	5
Retail	Shopping Center	Personal Vehicle	61
Retail	Strip Mall	Personal Vehicle	3
Workplace	General	Personal Vehicle	960
Workplace	High-Tech	Personal Vehicle	211
Government	Government Fleet	Government Vehicle	16
Municipal	Municipal Fleet	Government Vehicle	8
Municipal	Parks and Recreation (Public)	Government Vehicle	6

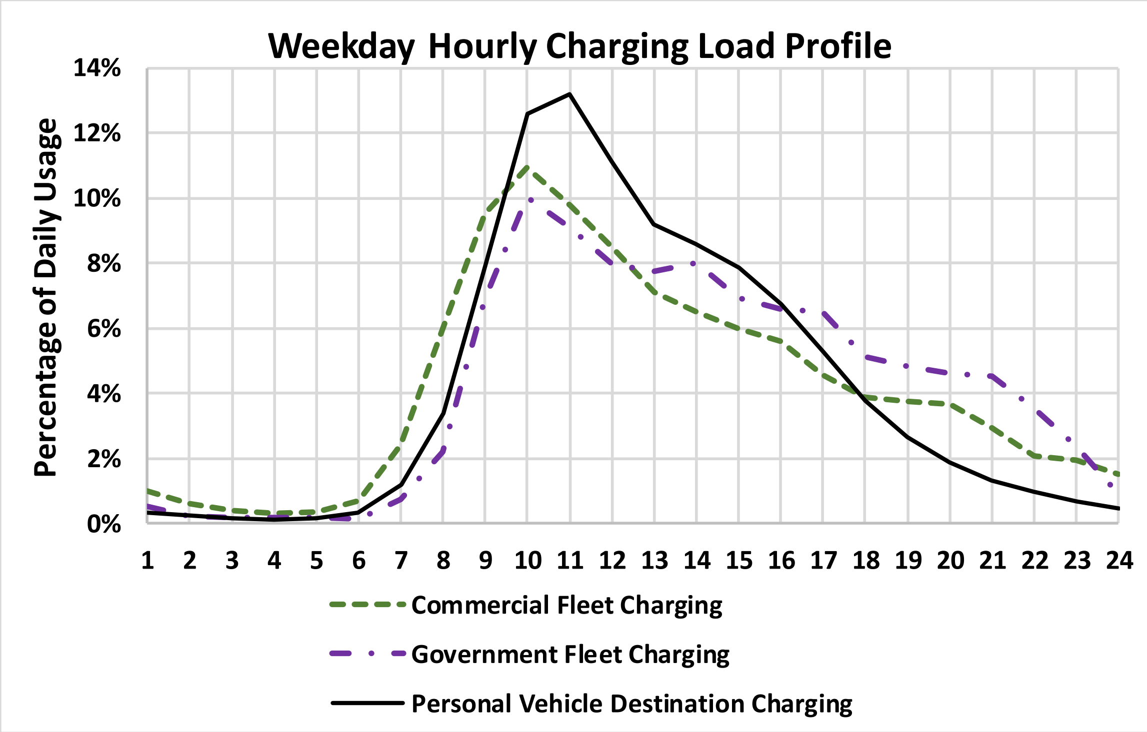
Classification of commercial categories, as provided by ChargePoint, into three classifications for use in this study.

Source: ADM Associates, Inc.

The weekday charging profiles for the three classifications are shown in

Figure 201.

Figure 201: 2017 Non-residential Weekday Charging Profiles for Three Types of Light Duty Vehicles



Typical hourly load shapes in summer weekdays for personal vehicles charging at commercial destinations (solid profile), for commercial fleets (dashed profile) and government fleets (dot-dashed profile).

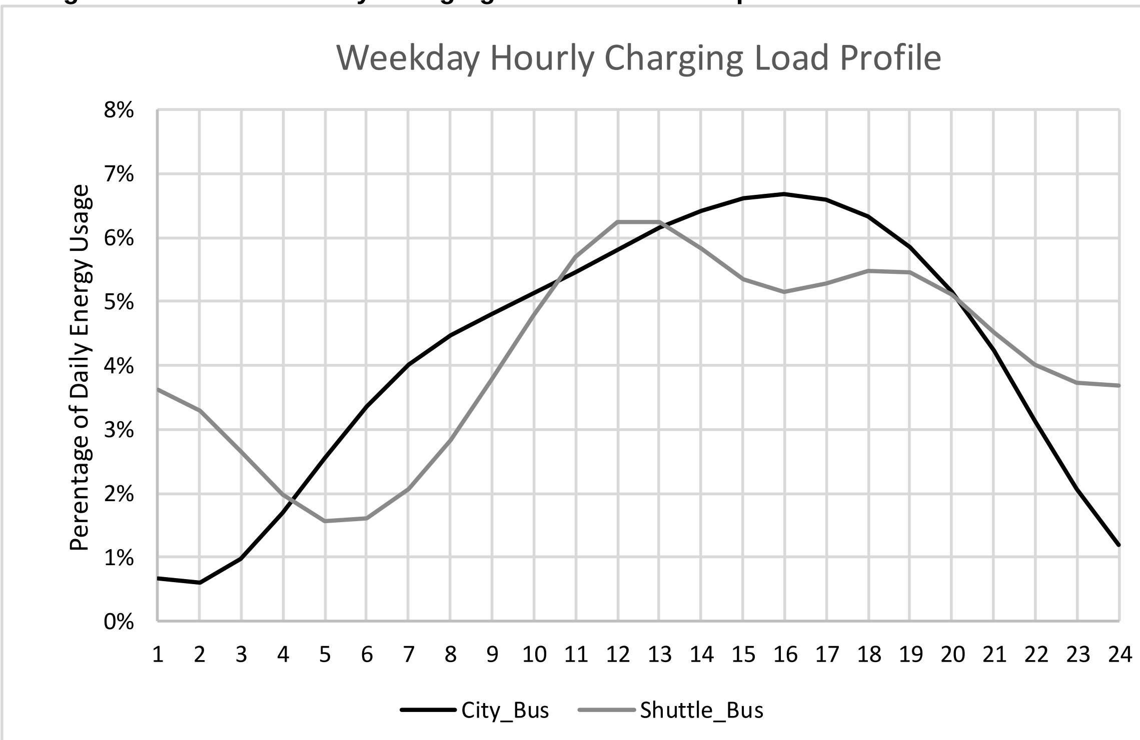
Source: ADM Associates, Inc, data from ChargePoint

Municipal Bus Charging Load Shapes

ADM obtained trending data from one municipal fleet of 14 heavy-duty busses, and five fleets of medium-duty shuttle busses. The five fleets included city-operated busses, private and government research and development campus employee shuttles, airport parking shuttles. The average weekday charging profiles for the busses and shuttles are shown in

Figure 202.

Figure 202: 2018 Weekday Charging Profiles for Municipal Busses and Shuttle Fleets



Typical hourly load shapes in weekdays for heavy duty municipal busses (dark profile), and for shuttle fleets (light profile).

Source: ADM Associates, Inc

Load Shape Specification and Creation

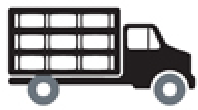
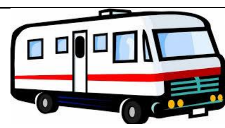
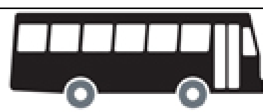
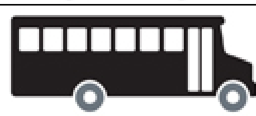
Light Duty Vehicles

Load shapes for light duty vehicles are developed from the ChargePoint data, as discussed previously. The load shapes are developed by compiling average hourly demand values for weekdays and weekend days for three types of locations: single family residential, multifamily residential, and personal vehicle destination charging. The hourly demand values are then normalized such that they sum to unity over all hours of a typical (non-leap) year. The light duty vehicle load shapes are applied to the portion of personal vehicle charging energy usage that occurs in the residential sector, and to the entire energy use of neighborhood electric vehicles.

Medium/Heavy Duty Vehicles

Medium-duty and heavy-duty vehicles represent a small percentage of the overall expected EV charging load. The group is heterogeneous in terms of operation and charging demands and schedules, as can be inferred by inspection of Table 7. In this table, the acronym GVWR denotes Gross Vehicle Weight Rating. Higher rating numbers indicate heavier vehicles.

Table 7: Listing of Medium and Heavy-Duty Vehicle Classes

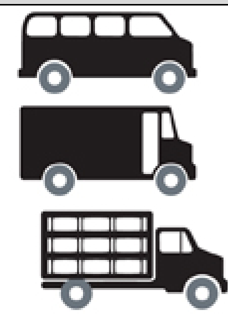
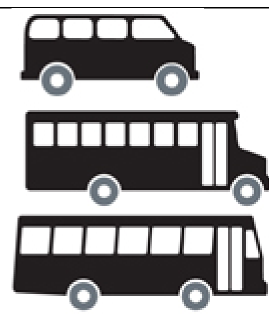
Vehicle Type	Typical Example	Electric Variant Likely?	Distinct Charging Energy Forecast?
GVWR3		Possible	Yes
GVWR4		Yes	Combined with 5
GVWR5		Yes	Combined with 4
GVWR-6		Possible	Yes
GVWR7		Possible	Yes
GVWR8 short-haul & Port		Yes	Yes
GVWR8 garbage		Possible	Yes
GVWR8 long-haul		Yes, Fixed Routes Only	No
Motorhomes (Class 3-7)		No	No
City Bus (Class 7)		Yes	Yes
School Bus (Class 6)		Yes	Yes
Shuttle (Class 3)		Yes	Yes

Description of medium and heavy-duty vehicles, whether an electric variant of the vehicle is likely, and whether a separate value is currently being modeled for the vehicle-type.

Source: ADM Associates, Inc. https://afdc.energy.gov/data/10381

Although ADM was able to collect primary data for municipal busses and shuttles, data for most of the categories above are not yet available. Even if distinct load shapes were available, however, the multiplicity of distinct types would lead to data processing and size issues. Given that medium and heavy-duty vehicles represent a small portion of the 2017 IEPR electric demand forecast for the transportation sector, the project team sought to limit the number of load shapes assigned to this sector to three. This is accomplished according to the grouping in Table 8.

Table 8: Grouping and Load Shape Construction for the Medium and Heavy-Duty Sector

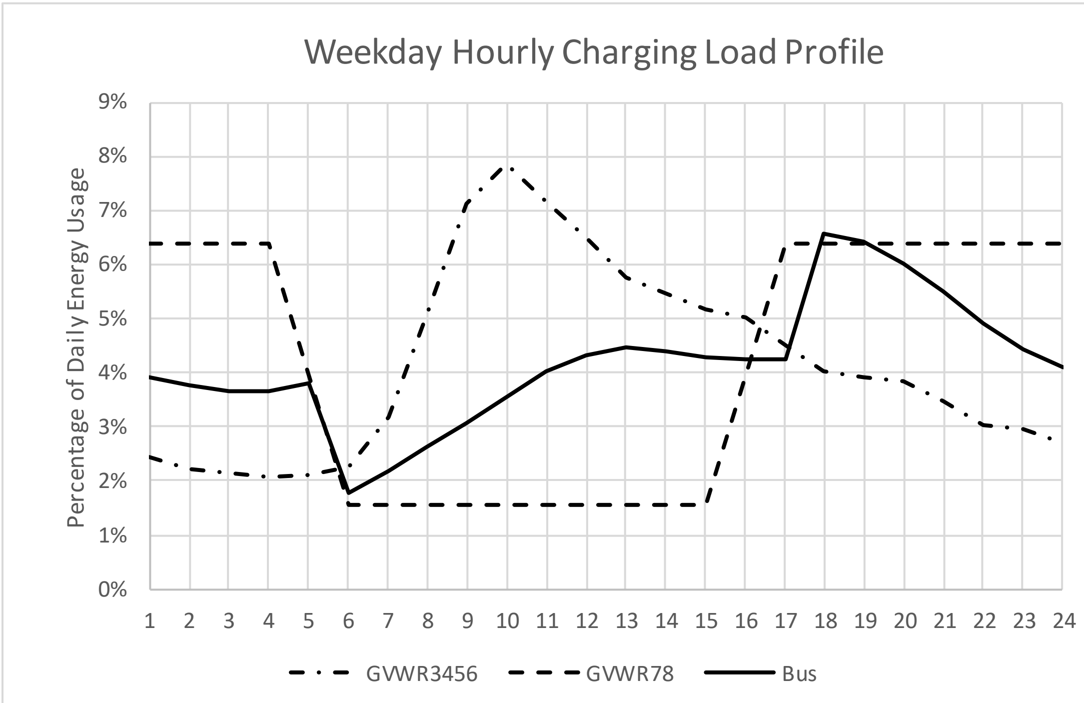
Vehicle Type	Typical Example	Preliminary Load shape
GVWR3,4,5,6		50%/50% Blend of the Commercial Fleet LDV profile, and a flat profile.
GVWR7,8		40%/40%/20% blend of a flat profile, a simulated profile for refuse truck, and a simulated profile for a short haul semi-truck.
Bus		40%/40%/20% blend of a municipal bus profile, the shuttle fleet profile, and a simulated school bus profile.

Description of medium and heavy-duty vehicle grouping for the development of EV load shapes.

Source: ADM Associates, Inc.

The three load shapes used for this sector are described in the last column of Table 8. The load shapes are blends of component profiles. Three of the component profiles—refuse trucks, short haul semi-trucks, and school busses—are simulated according to the assumption that charging occurs outside of the typical workday or school day. The blended profiles for the three aggregated classes are shown in Figure 205.

Figure 203: 2018 Weekday Charging Profiles for Busses and Medium and Heavy-Duty Vehicles



Typical hourly load shapes in weekdays for medium duty trucks in GVWR ratings 3-6 (dot-dashed profile) for heavy duty trucks (dashed profile), and for busses (solid profile).

Source: ADM Associates, Inc

Modeling Price Response

Price response is modeled through application of elasticity factors. A load shape is adjusted as follows:

$$A_h = \max\left(0,1 + TOU\% \times e \times (PR_h - 1)\right)$$

Where:

- A_h is the adjustment factor for hour h
- $TOU\%$ is the percentage of customers that have a TOU rate
- PR_h is the price ratio for hour h, defined as the price prevailing at hour h divided by the lowest available price for the given day, at the same location
- e is the Elasticity Factor

The *max* function sets a lower bound of zero for the adjustor[14]. The elasticity normalization leads to reduced electric demand during high-price periods. To preserve the overall forecast energy usage associated with charging, the load shapes are renormalized to unity after the price elasticity adjustment. Note that the type of price response modeled here is load shifting at the same location, rather than responding by charging at an alternate location during the same or comparable time period. The latter is addressed through adjustment of charging location shares for personal light duty vehicles.

As an example, if 100% of the customers are on TOU rates, and the elasticity factor is -0.7, and the price ratio is 2, then the adjustor is:

$$0.3 = \left(1 + 1 \times -0.7 \times (2 - 1)\right)$$

This indicates that the demand is 30% of what it would have been in the absence of TOU rates.

Elasticity factors are stored in a comma separated variable file, and take on separate values by forecast zone, year, and customer sector. The factors may be adjusted by Energy Commission staff. Default elasticity factors are -1.2 for the residential sector, and -0.6 for the commercial sector.

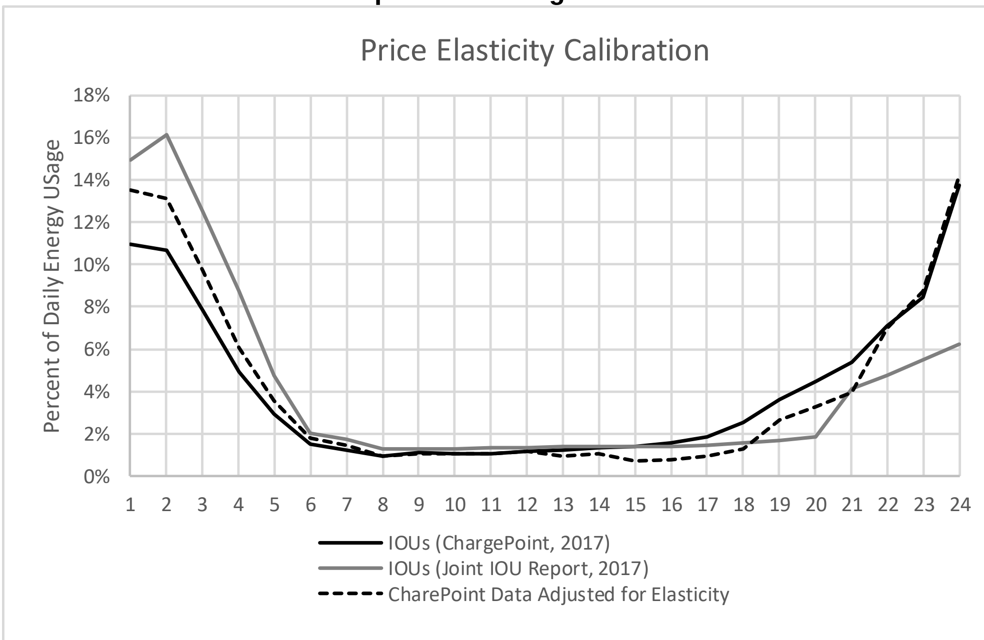
Utility rate structures are also stored in a comma separated variable files and vary by IOU and customer sector. The price response modeling occurs within the EV Infrastructure Load Model, as described in the following section.

Determination of Default Price Elasticity Factors

ADM has placed default factors for elasticities: -1.2 for the residential sector and -0.6 for the commercial sector. The factor for the residential sector was determined by comparing charging session data as obtained from ChargePoint to data from the Joint IOU report, as shown in Figure 204. The default elasticity factor for the commercial sector is set to be half that of the residential sector. Both factors can be updated as research results become available.

14 A dip below zero could be interpreted as customer's willingness to act as a capacity source during a demand response event. Negative values are not considered in the model at his time.

Figure 204: Comparison of Summer Weekday Charging Profiles Developed from the Joint IOU Report and ChargePoint Data



Typical hourly load shapes in summer weekdays for single family homes as from the Joint IOU report (light solid profile, averaged over all utilities) and ChargePoint (dark solid profile), and ChargePoint adjusted for price elasticity (dashed profile).

Source: ADM Associates, Inc, data from PG&E, SCE, SDG&E, and ChargePoint

The ChargePoint data appear to show more on-peak usage than the profiles in the Joint IOU Report, likely due to the fact that only a subset of ChargePoint customers are likely to be on time of use rates. Rate information is not available in the ChargePoint data, but the project team estimated that the fraction of ChargePoint customers on time of use rates is 32% as follows.

ADM cross referenced the numbers of customers on EV TOU rates in the year 2017, as reported in the Joint IOU Report (SDG&E, SCE & PG&E 2017), to the estimated number of EV in IOU service territories for 2017, as reported in the Energy Commission's Light Duty Plug-In Energy and Emission Calculator. The Joint IOU Report tallies to approximately 63,000 EV TOU accounts, compared to an estimated 266,000 EVs in service by the end of 2017, as estimated by the Energy Commission calculator.[15] Using these values, ADM estimated roughly 23.7% of EV customers being on TOU rates.

Customers with EV specific TOU rates account for 1% of total residential accounts for the IOUs. The Energy Commission estimates that about 9% of IOU customers were on TOU rates in 2017. Assuming that about 1% of the 9% estimate is attributable to the EV

15 Sales in 2017 are estimated, actual Department of Motor Vehicles registration data from 2011-2016 are adjusted for attrition

specific TOU rates, it is likely that an additional 8% of ChargePoint customers are on TOU rates, for a total of 31.7%.

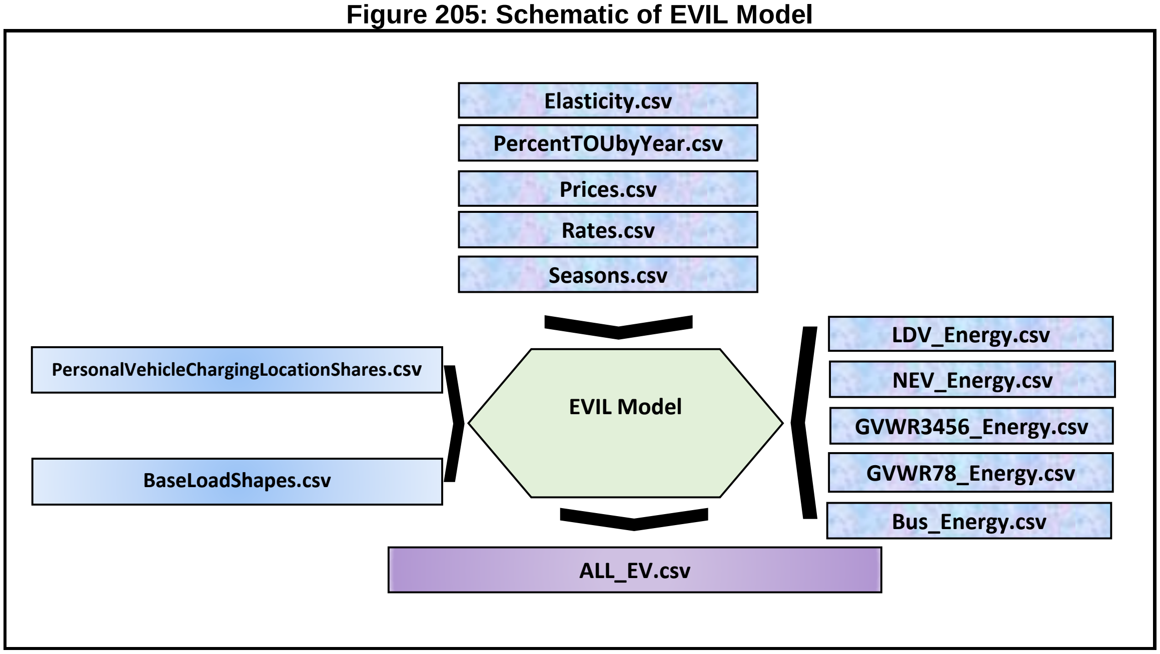
ADM calibrated the default elasticity parameter for the residential sector by varying the elasticity factor to minimize the relative root mean square error between the normalized Joint IOU load shape and the ChargePoint load shape during the hours of 12 PM to 9 PM (the hours that tend to have the highest electricity prices). An elasticity factor of -1.2 resulted in the best fit.

Calibration for the commercial sector is not possible. ADM has placed a default value of -0.6, or half the elasticity of the residential sector, with the reasoning that EV charging generally comprises a smaller portion of commercial customers' electric bills, and that vehicle availability requirements are less flexible for the non-residential sector. Energy Commission staff can override these default values by editing a simple data table as discussed in the next section.

Combining and Processing Forecast Elements

The CED Model has several elements that pertain to EV charging. ADM has developed a data input format, scenario specification tables and associated script in the R programming language to unify the forecast elements and generate EV load shapes. Together, these are named the EVIL Model. The EVIL Model, depicted in Figure 205, has three sets of input files.

Figure 205: Schematic of EVIL Model



A schematic of the EVIL Model.

Source: ADM Associates, Inc

In the right of the diagram are a set of five input files that describe forecast energy usages by vehicle classification, forecast zone, and year. The file *LDV_Energy.csv*, corresponding to light duty vehicles, is the most detailed and accounts for the most energy usage. The file includes one column to designate scenario, one column to designate forecast zone, one column to designate the type of vehicle, and then a number of columns that list forecast energy usages by year. Three types of vehicles are listed in this file:

- Personal vehicles—privately owned cars and light trucks
- Commercial vehicles—cars and light trucks owned by businesses
- Other vehicles—cars and light trucks owned by government entities, but also include rental car fleets

In addition to the light duty plug-in electric vehicle forecast input file, there are four files that describe forecast energy usages for neighborhood electric vehicles, trucks in gross vehicle weight ratings three to six, trucks in gross vehicle weight ratings seven and eight, and busses. It is assumed that these forecast elements are available by scenario and year at the statewide level[16].

At the top of Figure 205 figure are a set of five files that describe economic parameters used in scenario analysis. The first file designates price elasticities for EV charging. The elasticity factors are specified by year, forecast zone, and customer sector (commercial and residential). The next four files concern forecast assumptions regarding time of use rates. The file *Seasons.csv* defines seasons by month and utility company. The three seasons are Summer, Winter, and "MarchApril", which is necessitated by some SDG&E rates that have special hour designations in March and April. The file *Rates.csv* assigns the peak types for each rate, season, and day type (weekdays and weekends). The peak types are standardized to the following:

- Super off peak
- Off peak
- Mid peak
- On peak
- Critical peak

Each distinct rate assigns different hours to last four categories, although the hour assignments are structurally similar with highest rates in summer afternoons and lowest rates at nights. The critical peak designation is not currently in use but is included in case critical peak pricing is to be modeled specifically for EV charging.

16 Conversations with Energy Commission staff indicate that a finer geographical resolution may be possible for certain forecast elements, although the most recent results are at the statewide level. The EVIL Model distributes impacts by zone in proportion to light duty vehicle energy usage.

Finally, the file *Prices.csv* assigns prices and price ratios to the peak types for each rate. The price ratio is calculated as the ratio of the price in effect for a given hour, to the lowest price available during the same day.

The remaining two input files are the load shapes, which are assumed to be static, but can be updated as more data become available, and a file that distributes the total charging energy requirement for personal light duty vehicles into the single family residential, multifamily residential, and non-residential settings. The fractions can be modified for each year. Current default values are 68.9% for the single-family residential sector, 7.7% for the multifamily residential sector, and 23.4% for personal vehicle destination charging in the commercial sector. These values were determined by transcribing Figures 4.3 and 4.4 of the Energy Commission report *California Plug-In Electric Vehicle Infrastructure Projections: 2017-2025 CEC Staff Report* and by assuming that 90% of the charging in the residential sector occurs in single family homes (Bedir et al. 2018).[17]

Output Format

The EVIL model can output hourly loads associated with electric vehicle charging in several formats. At the most detailed level, the model can produce hourly loads for the entire forecast period. Although this is technically possible, the resulting data file can approach 1 Gigabyte (GB) in size. The number of data element scale as the product of each list element:

- The number of years in the forecast (13 years if 2018-2030)
- Three scenarios
- 8760 hours/year
- 12 forecast zones
- Six distinct load shapes

A file that contains all of the above data would have 341,640 rows associated with the scenarios and years, and 72 data columns with six load shapes per forecast zone.

It is important to recognize that the level of detail described is seldom necessary and by default the EVIL model outputs data in a condensed format. ADM has identified several ways to reduce file size while conveying the necessary information to Energy Commission forecasters. The first step of data reduction is to sum over residential and commercial sectors by zone. This reduces the six distinct load shapes to three, and generates a three-fold data reduction. The second step is to recognize that the EV load shapes for Monday to Friday are identical for any given month. Likewise, the profiles for Saturdays and Sundays are identical. While this may not actually be true, it is a necessary approximation. The rest of the forecast is largely weather dependent, while

17 Based on ADM's understanding of the forecast process, the single family/multifamily distinction is relatively unimportant, as most forecast metrics are at the sector and zone level, or at higher levels.

EV charging is generally not weather dependent. The particular peak day for the forecast is a function of the weather file, and not the day of the week (apart from the assumption that the peak occurs on a non-holiday weekday). The best way to treat weather-insensitive loads is in a probabilistic manner, which requires averaging over all weekdays. This allows a 15-fold data compression, as one requires only two representative days for each month.

CHAPTER 11:
Energy Efficiency Load Impact Profiles

Application of Base Load Shapes and Energy Efficiency Load Impact Profiles to Scenario Analysis

Base end-use load shapes, whole-building load shapes, and energy efficiency load impact profiles will all be used to characterize hourly impacts from codes, standards, and utility-sponsored energy efficiency programs. Much of the details surrounding the assignment of load profiles to codes, standards, and efficiency forecast elements may be automated with analysis scripts or spreadsheets. ADM has created a set of simple scripts, precursors to the HELM 2.0, that couple specific impact forecasts to appropriate load profiles. As one example, if a given AAEE forecast scenario expects 10 GWh of savings for the commercial HVAC end-use in PG&E service territory, a set of scripts will distribute the 10 GWh to all six forecast zones within PG&E service territory, and also to each of the 12 commercial building types within each zone. Each building and zone combination will be allotted a certain share of the overall 10 GWh in proportion to its energy use within the overall commercial sector for PG&E. For each building type and forecast zone, the total energy usage will also be divided into the major components that are described by the 'Commercial HVAC' category in AAEE: Cooling, Heat Pumps, Economizers, and Ventilation. The following sections motivate and describe this process. The specific tables that map elements from AAEE and Committed Savings forecast outputs to load shapes in HELM 2.0 are provided in Appendix B. Distribution of statewide or planning area impacts to forecast zones and building types depend on the base forecast output, year by year. The scripts that perform the disaggregation are provided as an electronic attachment to this report.

Characterization of Energy Efficiency Load Impact Profiles

Energy efficiency load impact profiles can be categorized as synchronous and asynchronous to the load shape associated with the targeted end-use(s). The degree of asynchronous behavior for a given energy efficiency measure will often determine the appropriate source and construction process for the related load impact profile.

Synchronous Measures

As an example, an exterior lighting wattage reduction will have a load impact profile that is synchronous with, and proportional to, the load shape for the targeted lights. Synchronous measures (and their load impact profiles) are well-represented by the associated end-use load shape. Some examples include:

- Lighting wattage reductions in unconditioned space

- HVAC system upgrades with systems that are more efficient, but not qualitatively different than the baseline systems (e.g. heat pump vs. heat pump, chiller vs. chiller)
- Most residential and commercial refrigeration measures that increase compressor efficiency or reduce thermal losses
- Most appliances and electronics

Near Synchronous Measures

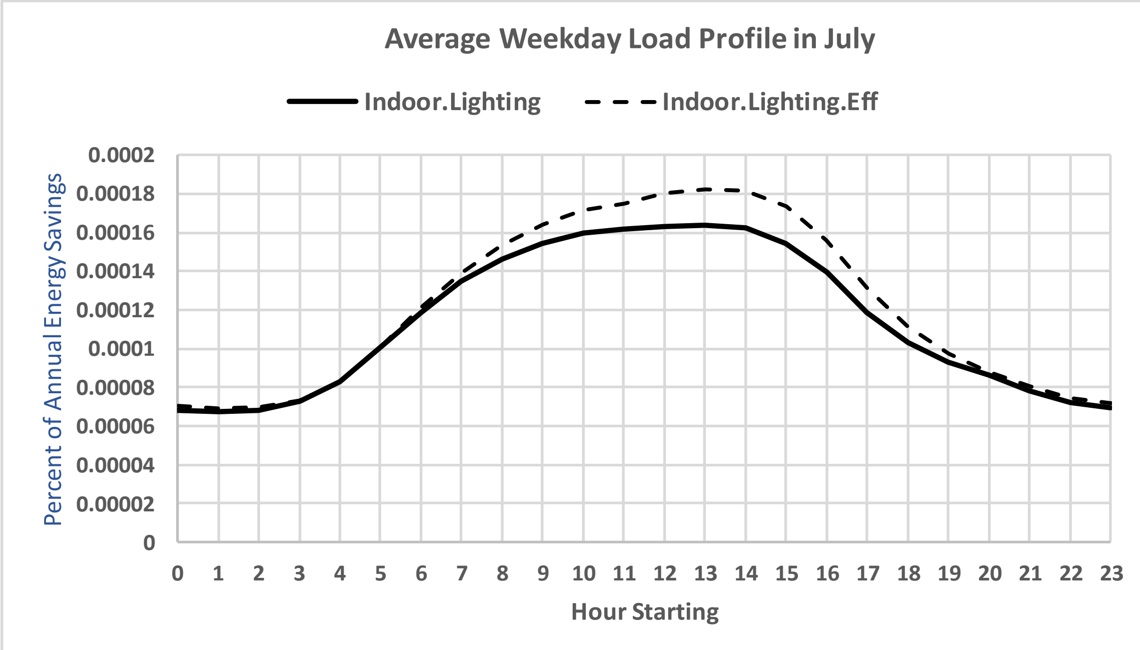
Some energy efficiency load impact profiles are nearly synchronous to the end-use load shape. In many applications within the industry, the load shapes are taken as first order approximations of these near-synchronous energy efficiency load impact profiles. Some examples of near-synchronous measures are listed below:

- Very high seasonal energy efficiency ratio (SEER) air conditioners or heat pumps—typically variable speed or variable refrigerant flow systems—may have very high coefficients of performance (COP), but only marginally higher energy efficiency ratios (EER), which are more closely correlated with peak demand savings.
- Lighting wattage reductions in conditioned space are mildly asynchronous due to HVAC interactive effects.
- Heat pump water heaters will generally have higher relative energy savings during summer than during winter, although most of the base energy usage occurs during the cooler months.
- In the residential sector, variable speed pool pumps tend to run longer hours, but at lower speeds than single-speed pool pumps. A given pool pump upgrade may have a load impact profile that differs from the load shape of either the baseline or efficient pumps. A large collection of pool pump upgrades, however, may be well-represented by the end-use load shape, as diversification tends to distribute impacts across hours.

An example of a near synchronous energy efficiency load impact profile is provided in

Figure 206. Interior lighting wattage reductions in the commercial sector tend to have similar shapes as the end-use load shape. However, reduced internal cooling loads due to the lighting energy savings tend to decrease air conditioner run-times, resulting in additional energy savings during the cooling season.

Figure 206: Comparison of Lighting Load Shape to Energy Efficiency Load Impact Profile



Typical hourly load shapes in July weekdays for interior lighting (solid profile) and interior lighting energy efficiency (dashed profile) for offices in forecast zone 3. Cooling interactive effects tend to increase impacts – particularly in afternoons.

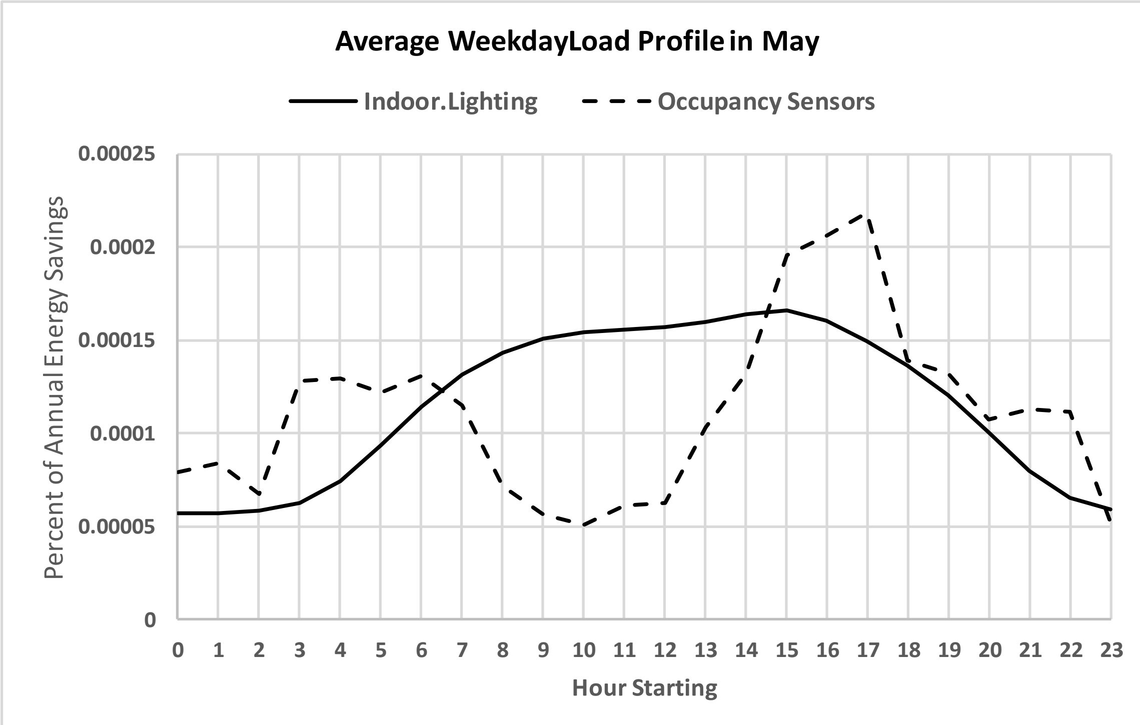
Source: ADM Associates, Inc.

Asynchronous Measures

Other types of energy efficiency load impact profiles will typically have impacts that are asynchronous to the load shapes of the targeted end-uses (Figure 209). Some examples include:

- Daylighting controls or lighting occupancy sensors
- Envelope improvement measures such as efficient windows or added insulation.
- Measures that involve fuel switching (for example air conditioner with a gas furnace replaced with heat pump)

Figure 207: Comparison of Lighting Load Shape and Occupancy Sensor Load Impact Profile



Typical hourly load shape in May weekdays for interior lighting (solid profile) and energy efficiency load impact profile for interior lighting occupancy sensor (dashed profile) for retail establishments in forecast zone 4. The load impact profile is largely asynchronous with the underlying end-use load shape.

Source: ADM Associates, Inc.

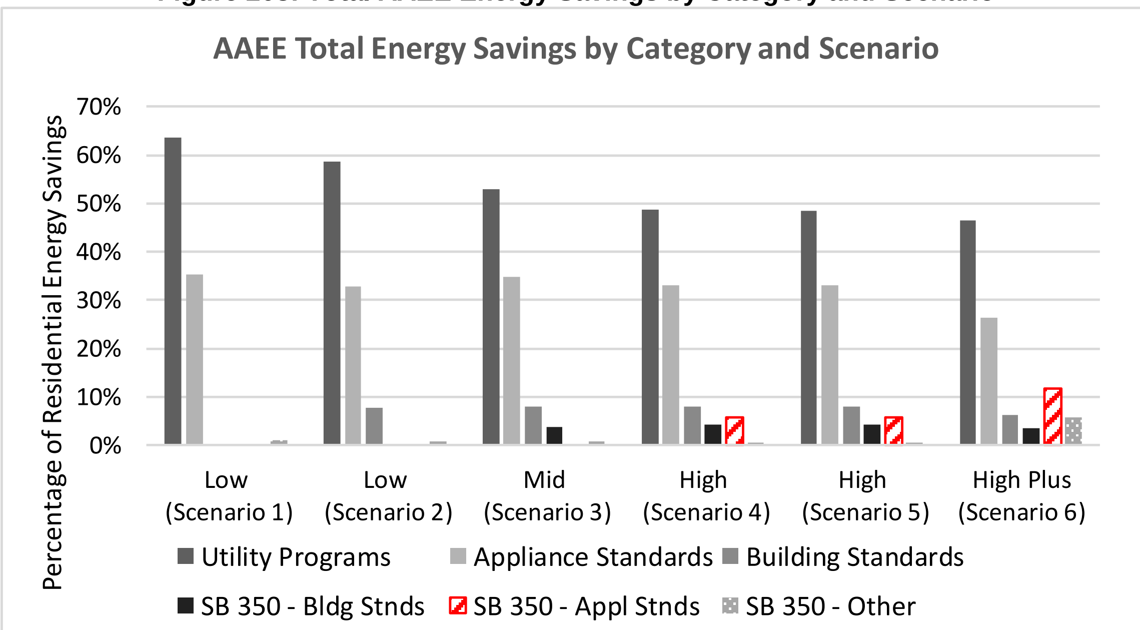
Review of Potential and Goals Study, AAEE, and Committed Savings

The CED Model includes 18 end-uses per zone for the residential sector and ten end-uses per zone for each of 12 building types in the commercial sector. Other sectors are considered at the whole building level. Potential energy efficiency measures, however, number in the hundreds for a given zone and building type combination. CED Model components for AAEE and committed savings, on the other hand, are at the sector and end-use level—a lower level of resolution than the demand forecast which is justified by the relatively small impact of energy efficiency compared to overall demand. ADM strove to balance the staggering multiplicity of individual energy efficiency measures described in the Potential and Goals Study[18], with the relatively low resolution of AAEE and committed savings forecast elements.

18 Wikler et al. 2017. *Energy Efficiency Potential and Goals Study for 2018 and Beyond.* California Public Utilities Commission. Reference Number: 174655

To identify the key sectors, end-uses, and measures to represent AAEE and committed savings, ADM reviewed the recent AAEE forecast elements from the 2017 Integrated Energy Policy Report (Bahreinian et al. 2018). The 2017 forecast included six AAEE scenarios. As a first step, ADM investigated the various agents of expected energy efficiency. As shown in Figure 208, in each of six forecast scenarios, utility-sponsored energy efficiency programs are expected to account for the most energy savings. Federal appliance standards are the next most significant component, followed by building standards.

Figure 208: Total AAEE Energy Savings by Category and Scenario



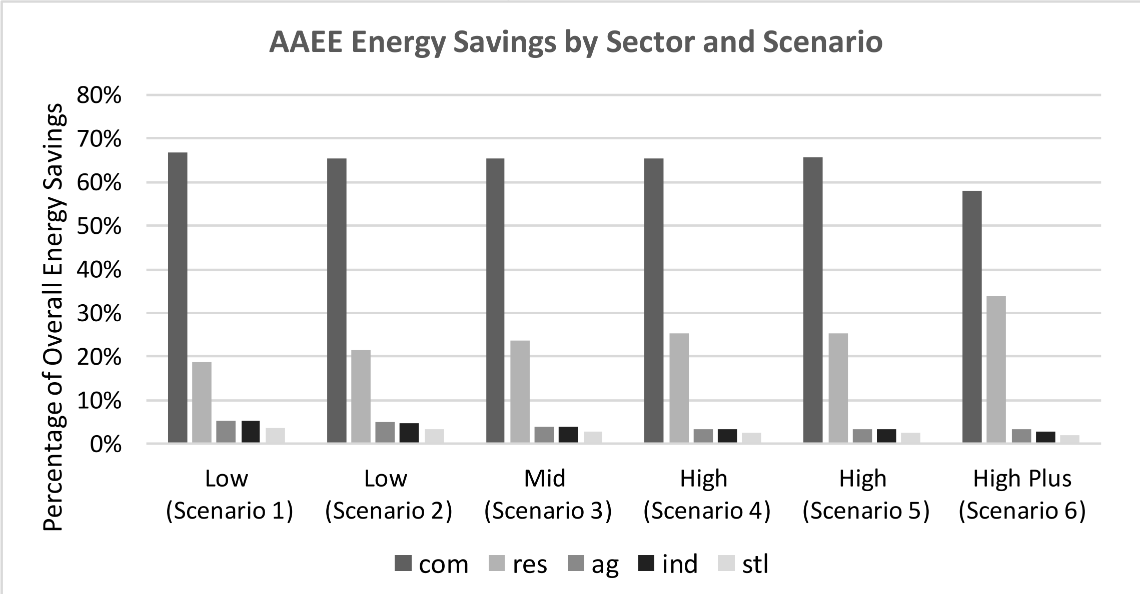
AAEE energy savings by savings category and scenario, taken from the 2017 Integrated Energy Policy Report (Bahreinian et al., 2018). Most impacts are concentrated in utility-sponsored programs and federal appliance standards.

Source: ADM Associates, Inc.

Utility-sponsored programs, federal appliance standards and existing building standards are described with relatively high resolution. Smaller components, such as future building standards or yet-undetermined legislatively-induced energy savings, are not specified in a manner to allow assignment of closely matched load shapes.

As a next step, ADM inspected the relative weight of overall energy savings by customer sector for each forecast scenario. In all scenarios, most energy savings accrue to the commercial sector, followed by the residential sector. All other sectors combined account for less than 15% of savings, in each scenario.

Figure 209: Total AAEE Energy Savings by Sector and Scenario, from the 2017 Integrated Energy Policy Report



AAEE energy savings by customer sector and scenario, taken from the 2017 Integrated Energy Policy Report (Bahreinian et al. 2018). Most impacts are concentrated in the commercial and residential sectors.

Source: ADM Associates, Inc.

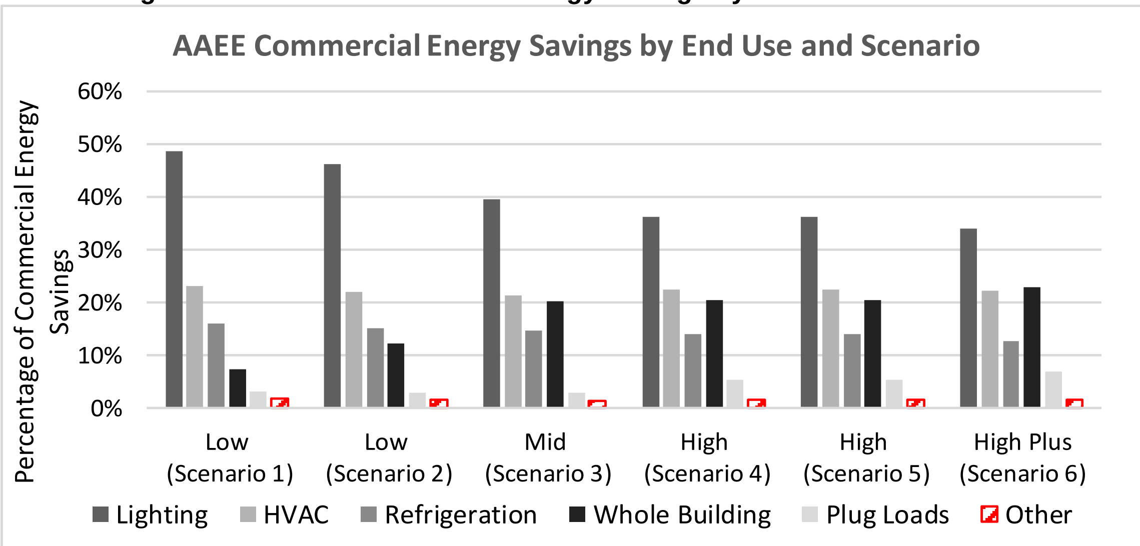
Given the importance of commercial and residential sectors, ADM looked more closely at the forecast AAEE savings for these two sectors.

Commercial Sector

In the commercial sector, much of the energy savings are attributable to lighting, HVAC, and refrigeration, as shown in

Figure 210. However, as the AAEE scenarios become more aggressive, energy efficiency that target the whole building, rather than any particular end-use, become more significant. Most of the energy savings in the whole building category are attributable to building standards and utility sponsored behavioral programs.

Figure 210: AAEE Commercial Energy Savings by End-Use and Scenario



Commercial AAEE energy savings by end-use and scenario, taken from the 2017 Integrated Energy Policy Report (Bahreinian et al. 2018). Most impacts are concentrated in the lighting, HVAC, refrigeration, and whole building savings.

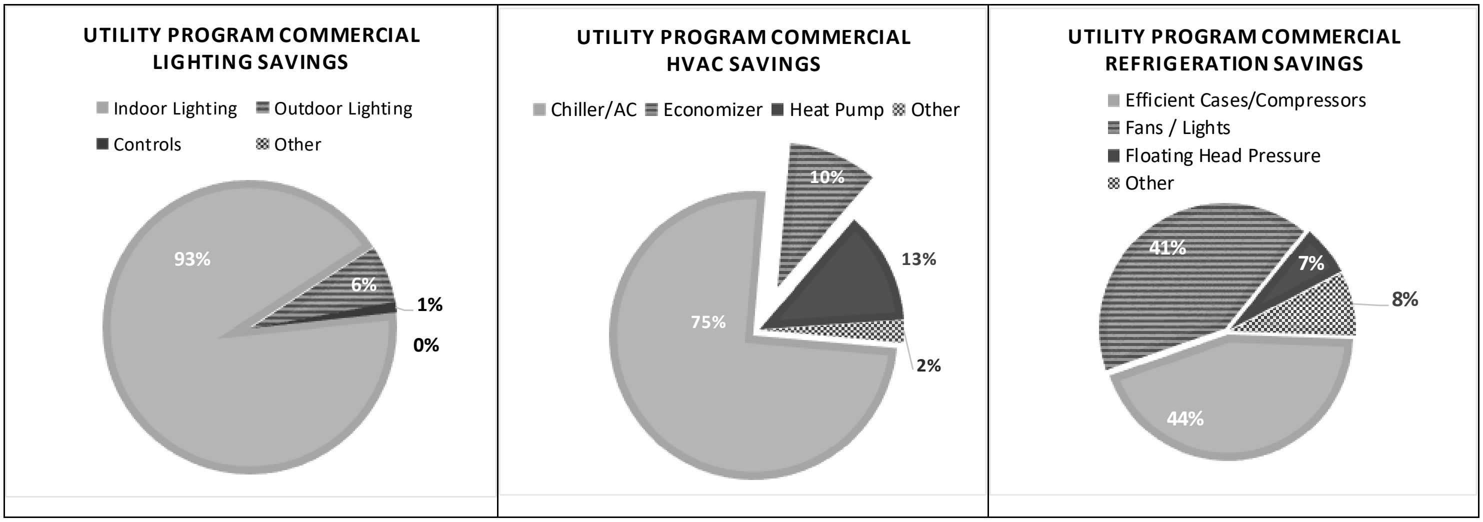
Source: ADM Associates, Inc.

Additional detail at the measure level is available in the appendices of the Potential and Goals Study (Wilker et al., 2017)[19]. ADM reviewed savings contributions of specific measures for the three most significant end-uses in the commercial sector. The results for utility-sponsored programs are shown in

Figure 211. Codes and standards based energy savings have similar patterns. It is interesting to note that most of the energy savings are attributable to efficiency improvements, such as lighting wattage reductions or more efficient compressors, rather than controls-based measures such as variable frequency drives or occupancy sensors. This is consistent with the project team's experience from evaluating commercial and industrial energy efficiency programs across the country.

19 ADM found the following excel summary to be particularly helpful: ftp://ftp.cpuc.ca.gov/gopher-data/energy_division/EnergyEfficiency/DAWG/2018_PG%20Study%20Measure%20Level%20Results%20Final_092517.xlsx

Figure 211: Utility Program Savings by Specific Measure for Major End-Uses in the Commercial Sector



Utility-sponsored commercial sector energy savings for the lighting, HVAC, and refrigeration end-uses, lighting, HVAC, and refrigeration end-uses, broken down into specific measures by inspecting the Potential and Goals Study measure level results viewer for the 'mTRC (GHG adder 1)' scenario.

Source: ADM Associates, Inc.

Based on the previous findings summarized, ADM identified much of the energy savings associated with outdoor lighting, HVAC, and refrigeration area characterized as synchronous, and can be represented with corresponding end-use load shapes. A special load impact profile is warranted for indoor lighting, as it is the most significant energy savings component, and the impacts are near-synchronous, but not synchronous with the end-use load shape. ADM also developed separate energy efficiency load impact profiles for daylighting and occupancy sensors, as these are asynchronous measures which are not well-represented by the end-use load shape. For HVAC energy efficiency measures, ADM developed economizer and heat pump energy efficiency load impact profiles. A heat pump energy efficiency load impact profile is necessary primarily because the heating and cooling end-use load shapes are treated as separate end-uses, while a heat pump will save on both end-uses, with the fraction of heating and cooling savings varying by building type and geographical location. ADM also developed whole building energy efficiency load impact profiles, which can be used to represent behavioral programs and expected but unspecified building standards. Finally, a "flat" energy efficiency load impact profile was provided to represent savings for various energy efficiency measures that are essentially constant in impacts, such as parking garage lighting upgrades, efficient data centers, and (as a good approximation) process-related air compressors. Table 9 lists base and efficiency load shapes for the commercial sector.

Table 9: List of Load Shapes Used to Model Commercial Sector AAEE Savings

Base End-use Load Shapes		Energy Efficiency Load Impact Profiles
		Daylighting
		Occupancy Sensor
Heating	Refrigeration	Lighting Efficiency
Cooling	Indoor Lighting	Heat Pump
Ventilation	Miscellaneous	Economizer
Water Heating	Office Equipment	Whole Building
Cooking	Outdoor Lighting	Flat

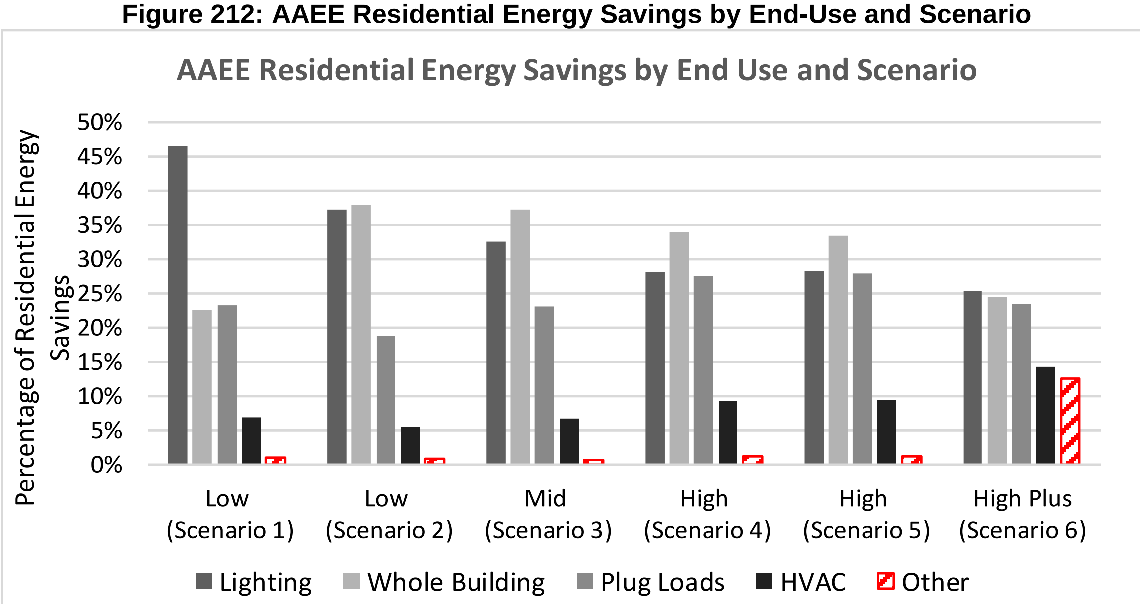
A list of base and efficiency load shapes for the commercial sector.

Source: ADM Associates, Inc.

Residential Sector

In the residential sector, much of the energy savings are also attributable to lighting, whole building, and plug loads, as shown in Figure 212. However, as the AAEE scenarios become more aggressive, lighting comprises a smaller portion of the savings while other measures become more significant. Most of the energy savings in the “other” category is attributable to building standards and utility sponsored behavioral programs.

Figure 212: AAEE Residential Energy Savings by End-Use and Scenario

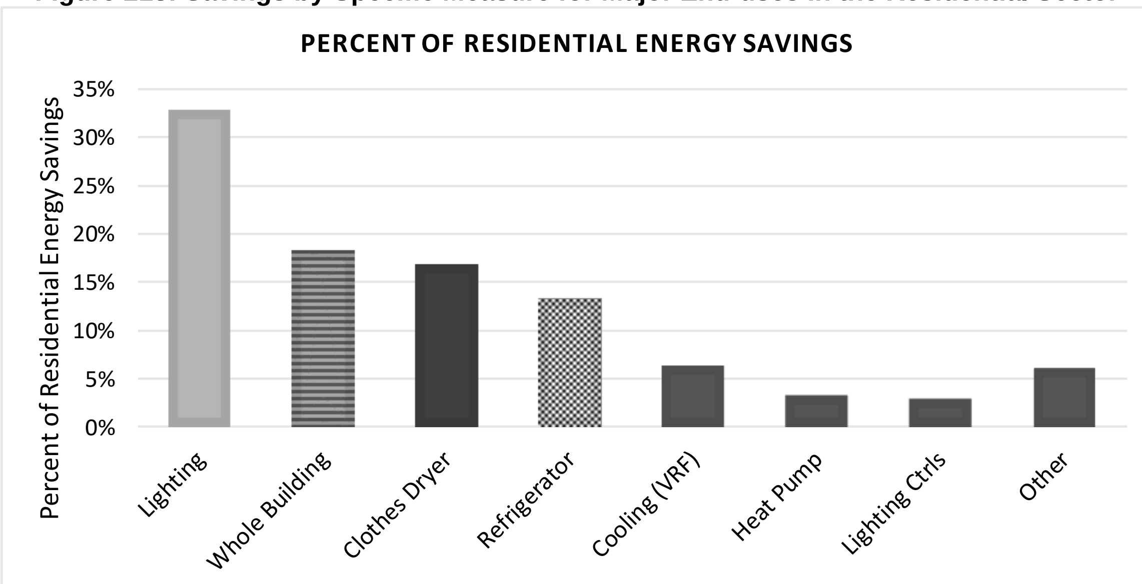


Residential AAEE energy savings by end-use and scenario, taken from the 2017 Integrated Energy Policy Report (Bahreinian et al., 2018). Most impacts are concentrated in the lighting, plug loads, and whole-building.

Source: ADM Associates, Inc.

Consulting the Potential and Goals Study (Wikler et al. 2017), ADM found that the most significant energy efficiency measures are lighting upgrades, whole building savings (mostly form behavioral programs), and appliances like clothes dryers and refrigerators (Figure 215). A relatively small portion of the savings were attributable to high efficiency (often variable refrigerant flow) air conditioners and heat pumps, and to lighting controls.

Figure 213: Savings by Specific Measure for Major End-uses in the Residential Sector



Residential sector energy savings broken down into specific measures by inspecting the Potential and Goals Study (Wikler et al. 2017) measure level results viewer.

Source: ADM Associates, Inc.

Of the measures listed, clothes dryers and refrigerators are adequately represented by base end-use profiles. ADM identified several energy efficiency load impact profiles that would be required to characterize residential impacts from AAEE. As with the commercial sector, a special energy efficiency load impact profile is warranted for indoor lighting, as it is the most significant energy savings component. ADM also developed whole building load shapes, which can be used to represent behavioral programs and expected but unspecified building standards. In the HVAC sector, ADM developed variable refrigerant flow air conditioner and heat pump energy efficiency load impact profiles to capture the expected increase in market share for these technologies. These technologies tend to cause significant energy savings during part-load operation conditions, and therefore application of end-use load shapes would result in overestimation of peak demand reductions from these measures. Although residential occupancy sensors, insulation improvements, or efficient windows do not account for a significant portion of expected impacts, ADM develop load impact profiles for these measures for completeness, as these measures are asynchronous with the end-use load shape and are not well represented.

Table 10 lists end-use load shapes and energy efficiency load impact profiles for the residential sector.

Table 10: List of Load Shapes Used to Model Residential Sector AAEE Savings

Base End-use Load Shapes		Energy Efficiency Load Impact Profiles
Cooking	Pool Heater	
Cooling	Pool Pump	
Dishwasher	Refrigerator	Whole Building
Dryer	Solar Pool Pump	Insulation
Freezer	Spa Heater	Lighting Efficiency
Furnace Fan	Spa Pump	Efficient Windows
Heating	Television	Heat Pump (high SEER/VRF)
Lighting	Washer	Cooling (high SEER/VRF)
Miscellaneous	Water Heater	Occupancy Sensor

A list of base and efficiency load shapes for the residential sector.

Source: ADM Associates, Inc.

Other Sectors

The TCU, mining and extraction, and industrial sectors are described only with whole building end-use load shapes. Accordingly, whole building load shapes are also used to characterize AAEE and committed savings for these sectors. The streetlighting sector is described with one load impact profile, which serves as the end-use profile and the energy efficiency load impact profile.

Additional Considerations in Load Impact Profile Selection

The energy efficiency load impact profiles in the last columns of **Table 9** and

Table 10 are winnowed from a broader list of candidate load impact profiles. ADM made the following considerations to retain or discard candidate profiles:

1. Does the candidate load impact profile correspond well to measures that describe a significant portion of energy savings described in the Potential and Goals Study (Wikler et al., 2017)?
2. Does the candidate load impact profile represent a significant improvement over the best matching end-use load shape? For example, is it asynchronous with the targeted end-use?
3. Are there sufficient data or simulation tools to construct the candidate profile?
4. Are there any other candidate load impact profiles that can serve the same purpose?

The above considerations are demonstrated in an example below. The example involves utility company sponsored energy savings for the HVAC end-use in the commercial sector. Table 11 lists the energy efficiency measures that account for the top 95% of energy savings through the year 2030 associated with utility-sponsored programs. The last column shows candidate load shape assignment. In the project naming convention, load impact profiles that have been developed specifically for use as energy efficiency load impact profiles have the ".Eff" suffix.

Table 11: Measures in the Potential and Goals Study that Account for the Top 95% of Commercial HVAC Energy Savings

Utility Sponsored Program Measure	Percent of Total Energy Savings	Candidate Load Impact Profile
Com | Split System AC (SEER 22)	26%	Cooling
Com | Efficient Chiller	16%	Cooling
Com | Split System AC (SEER 18)	15%	Cooling
Com | Split System AC (SEER 16)	14%	Cooling
Com | Economizer	10%	Economizer.Eff
Com | HVAC Quality Maintenance (Elec SH)	9%	Heat.Pump.Eff
Com | Split System AC (SEER 14)	2%	Cooling
Com | Packaged RTU AC (IEER 14.0)	1%	Cooling
Com | Ductless Mini Split Heat Pump (SEER 18)	1%	Heat.Pump.Eff
Com | HVAC Motor - ECM	1%	Ventilation

List of measures in the Potential and Goals Study that account for the top 95% of the commercial HVAC energy savings projected through 2030 and their respective candidate load impact profiles.

Source: ADM Associates, Inc.

After assigning candidate load shapes to each listed measure (including a number of measures not listed above, that account for the last 5% of energy savings), the candidate load impact profiles are assessed by reviewing the total energy savings represented by load shape, as shown in Table 12.

Table 12: Percent of Overall Commercial HVAC Energy Savings by Candidate Load Shape

Candidate Load Shape	Percent of Savings
Cooling	75.01%
Heat.Pump.Eff	12.60%
Economizer.Eff	9.91%
Thermostat.Eff	1.64%
Ventilation	0.81%
Ground.Source.Heat.Pump.Eff	0.01%

List of contribution to commercial HVAC savings by candidate load shape.

Source: ADM Associates, Inc.

Referring to Table 12, a quick observation is that the *Ground.Source.Heat.Pump.Eff* candidate load impact profile, which represents ground source heat pumps, is distinct from the overall *Heat.Pump.Eff* profile which represents efficient air source heat pumps. Ground source heat pumps have different part-load curves than air-source heat pumps. Notably, they have distinct advantages during extreme temperatures. The expected energy savings from ground source heat pumps amounts to 0.01% of the total for the HVAC end-uses, however. Applying the four considerations above, it can be concluded that:

1. The ground source heat pump candidate load shape does not represent a significant portion of the expected energy savings.
2. The ground source heat pump candidate load shape offers an advantage over the existing end-use profile. In fact, there is no heat-pump end-use profile, only heating, cooling, and ventilation.
3. The ground source heat pump energy efficiency measure can be simulated within the EnergyPlus framework.
4. The *Heat.Pump.Eff* candidate profile would be quite similar to a ground source heat pump profile, and solves the problem identified in item #2 above.

After the four considerations above, ADM decided to discard the ground source heat pump candidate load impact profile and to re-assign its weight to air source heat pumps.

The same considerations are applied to the thermostat and ventilation candidate load impact profiles. ADM found that smart thermostats cannot reliably be simulated by EnergyPlus, and also that they represent a small portion of the overall savings. ADM selected the ventilation end-use load shape as a reasonable proxy. The economizer and heat pump candidate energy efficiency profiles were generated in the EnergyPlus/R framework as described in the next section.

Development of Energy Efficiency Load Impacts

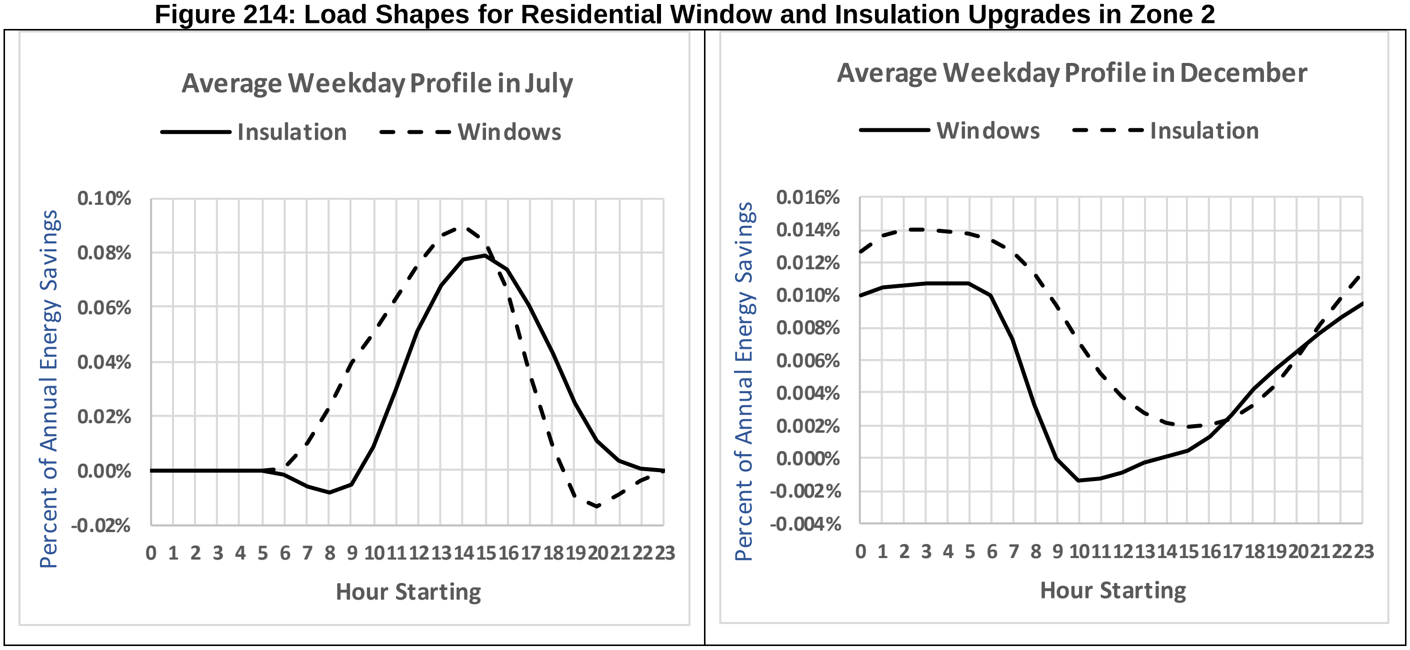
ADM utilized the same EnergyPlus/R framework that was used to develop load shapes to develop most of the energy efficiency load impact profiles. The basic process is provided in the following generalized steps. Please note that the process may involve dozens or hundreds of runs for a given measure.

1. Run EnergyPlus parametric models in “baseline” mode
2. Run same EnergyPlus parametric models in “efficient” mode
3. Calculate the hourly difference in above sets of runs at the whole-building level
4. Regress on the hourly difference to cast it as an energy efficiency load impact profile generator

The specific regression models may have varying structures. For example, an economizer model acts as a modifier on the cooling load shape and is therefore a function of the underlying cooling load shape and the outside air temperature.

Figure 214 shows load impact profiles for efficient windows and attic insulation for single family homes in forecast zone 2.

Figure 214: Load Shapes for Residential Window and Insulation Upgrades in Zone 2



Energy efficiency load impact profiles for single family residences in forecast zone 2 for attic insulation (solid profile) and efficient windows (dashed profile) in July (left plot) and December (right plot).

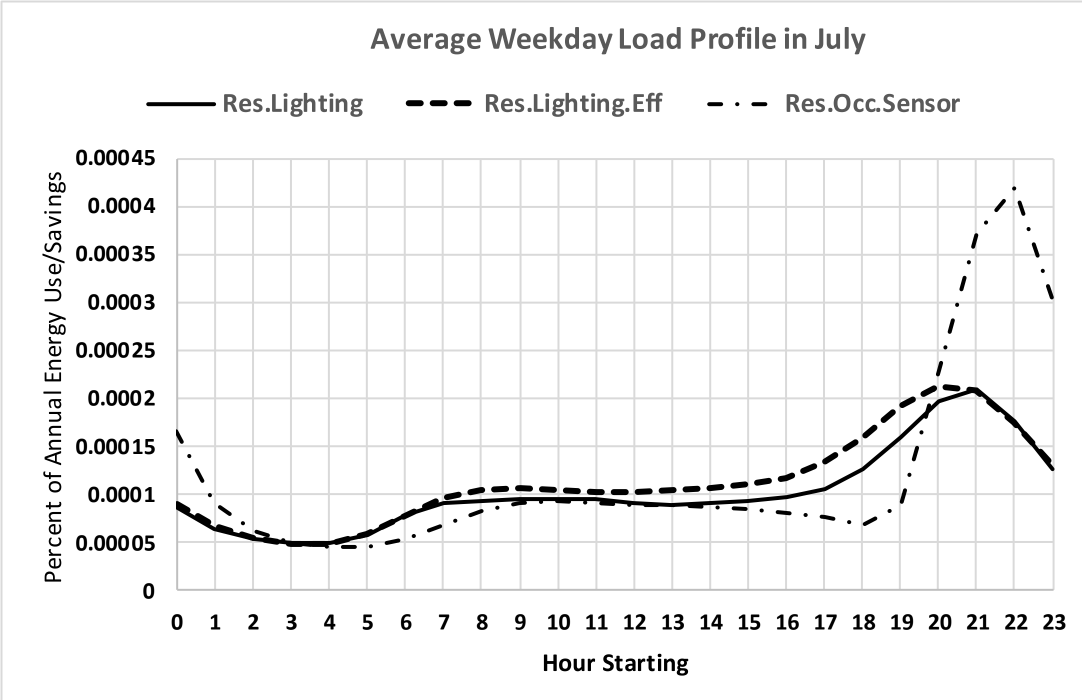
Source: ADM Associates, Inc.

Lighting Occupancy Sensor Load shapes

The process above describes the development effort for most energy efficiency load shapes. The lighting occupancy sensor load shapes, however, required significant data collection and processing in advance of running the EnergyPlus models. To estimate energy efficiency load impact profiles for occupancy sensors, ADM reviewed lighting logger data from hundreds of lighting loggers installed for measurement and verification of energy efficiency programs across the country. Each of the data loggers was installed on a fixture that was controlled by an occupancy sensor. ADM imputed the baseline schedule, following a process that ADM has devised for measurement and verification of commercial lighting projects, and then determined hourly multipliers for weekdays and weekends. For example, a multiplier of 0.7 indicates that occupancy sensors achieve a 30% on-time reduction for a given hour. The multipliers were then applied to base load shapes by matching annual hours' baseline hours of use to building types based on typical operation profiles. In this step, logger data were categorized into short, medium, or long hours of use, and schools and offices were assigned the savings factors from loggers with shorter hours of use, college and retail were assigned medium hours of use, and all other building types were assigned the savings factors derived from loggers that had longer hours of use. The modified base load shapes were then fed into EnergyPlus simulations described previously.

Lighting occupancy sensors represent a much smaller portion of residential sector energy savings. Despite having conducted lighting metering studies, ADM did not have primary data available to characterize the impacts of occupancy sensors. ADM developed a residential lighting occupancy sensor profile by assuming that a disproportionate amount of the energy savings occurs during times that are associated with declines in lighting use (8 PM to 3 AM). The savings profile was then put through the four-step process listed above to add interactive effects (Figure 217).

Figure 215: Residential Lighting Load Shape, Lighting Efficiency Impact Profile, and Occupancy Sensor Impact Profile



Residential lighting base end-use load shape (solid profile), efficiency load impact profile (dashed profile, buoyed by cooling interactive effects), and occupancy sensor efficiency load impact profile (dot-dashed profile).

Source: ADM Associates, Inc

Application of Energy Efficiency Load Impact Profiles

As described in APPENDIX A:

HELM 2.0 Manual, the HELM 2.0 framework allows any available load shape to be coupled with any given energy usage or savings amount by year, forecast zone, and customer sector. However, ADM has developed a set of data tables in comma separated variable format and associated scripts in the R programming language to assign impacts from AAEE scenarios and committed savings to appropriate load impact profiles, and to distribute these among forecast zones. To assign load impact profiles, ADM first reviewed the incoming data from the CED Model process for AAEE and committed savings. The AAEE file structure is shown in Table 13.

Table 13: Excerpt of AAEE Spreadsheet from the 2017 IEPR Forecast

Scenario Name	Utility	Sector	Category 1	Category 2	Conventional or Emerging	End-use	GWh by 2030
Mid-Mid	PG&E	Com	Equipment	Utility Programs	Conventional	Lighting	1,325
Mid-Mid	PG&E	Com	Codes and Standards	Appliance Standards		Lighting	609

Mid-Mid	PG&E	Com	SB 350 - Prop 39	Prop 39		Lighting	46
Mid-Mid	PG&E	Com	Equipment	Utility Programs	Emerging	Lighting	8

An excerpt of the AAEE spreadsheet from the 2017 IEPR Forecast which illustrates the GWh savings projected for commercial lighting.

Source: ADM Associates, Inc.

The energy savings are characterized by end-use and also by two categories. Recall that utility programs account for most of the expected energy savings and that the remaining categories are largely due to codes and standards, notably federal appliance standards and California building standards. ADM combined the three data fields *Category 1*, *Category 2*, and *Conventional or Emerging* as follows: Any line item that is described as a utility program under *Category 2* is designated as "Utility" and all other line items are categorizes as "Other", with the understanding that the "Other" category is dominated by codes and standards. ADM then consulted the Measure Level Results Appendix of the Potential and Goals Study (Wikler et al. 2017), and reviewed the utility sponsored measures and the codes and standards measures for each end-use and sector. Note that the Potential and Goals Study also includes behavioral programs, but the impacts from behavioral programs are modeled with whole building load impact profiles rather than end-use specific profiles. Table 14 demonstrates how load impact profiles are assigned to the two middle rows of Table 13. ADM used six distinct load impact profiles that may characterize energy savings for commercial lighting. ADM assigned weights to load impact profiles for each code-based energy efficiency measure. The weights in each row sum to 100%. For example, 100% of the sky-lighting measure is described with the Daylighting.Eff load impact profile, while the non-residential alterations are distributed to indoor and outdoor lighting, occupancy sensors, and daylighting.

Table 14: Load Shape Assignment for Commercial Lighting Codes and Standards

Codes and Standards Measure for Commercial Lighting	Indoor.Lighting.Eff	Outdoor.Lighting	Daylighting.Eff	Occsensor.Eff	Flat
2013 T-24: NRA-Lighting-Alterations-New Measures	80%	10%	1%	9%	0%
2013 T-24: NRA-Lighting-Alterations-Existing Measures	80%	10%	1%	9%	0%
2013 T-24: NRA-Lighting-Egress Lighting Control	5%	5%	0%	90%	0%
Future T-20: Small Diameter Directional Lamps (Tier 1)	100%	0%	0%	0%	0%
2016 T-24 -NRA-Lighting-Alterations	80%	10%	1%	9%	0%
2013 T-24: NRNC-Lighting-Controllable Lighting	0%	0%	10%	90%	0%
2013 T-24: NRNC-Lighting-Egress Lighting Control	5%	5%	0%	90%	0%
2013 T-24: NRA-Lighting-Warehouses and Libraries	80%	10%	1%	9%	0%
Fed Appliance: General Service Fluorescent Lamps #2	95%	5%	0%	0%	0%
2008 T-24: Tailored Indoor lighting	100%	0%	0%	0%	0%
2013 T-24: NRNC-Lighting-Warehouses and Libraries	80%	3%	2%	15%	0%
2008 T-24: Skylighting	0%	0%	100%	0%	0%
Fed Appliance: General Service Fluorescent Lamps #1	95%	5%	0%	0%	0%
2013 T-24: NRNC-Lighting-Office Plug Load Control	0%	0%	0%	100%	0%
Fed Appliance: Fluorescent Ballasts	95%	5%	0%	0%	0%
2013 T-24: NRNC-Lighting-Parking Garage	0%	0%	0%	0%	100%
2008 T-24: Sidelighting	10%	0%	90%	0%	0%
2016 T-20: Dimming Ballasts	25%	25%	25%	25%	0%
2013 T-24: NRNC-Lighting-MF Building Corridors	0%	0%	0%	0%	100%
2013 T-24: NRNC-Lighting-Outdoor Lighting & Controls	0%	100%	0%	0%	0%
2013 T-24: NRA-Lighting-MF Building Corridors	0%	0%	0%	0%	100%
2008 T-24: Outdoor Lighting	0%	100%	0%	0%	0%
Fed Appliance: Metal Halide Lamp Fixtures	50%	50%	0%	0%	0%
2016 T-24 -NRA-Lighting-ASHARE Measure-Elevator Lighting & Ventilation	0%	0%	0%	0%	100%
2016 T-24 -NRA-Lighting-Outdoor Lighting Controls	0%	100%	0%	0%	0%
2013 T-24: NRA-Lighting-Hotel Corridors	0%	0%	0%	0%	100%
2005 T-24: Lighting controls under skylights	0%	0%	100%	0%	0%

A list of commercial lighting codes and standards reported in the Potential and Goals Study and their relative assignment to ADM's lighting-related energy efficiency load impact profiles.

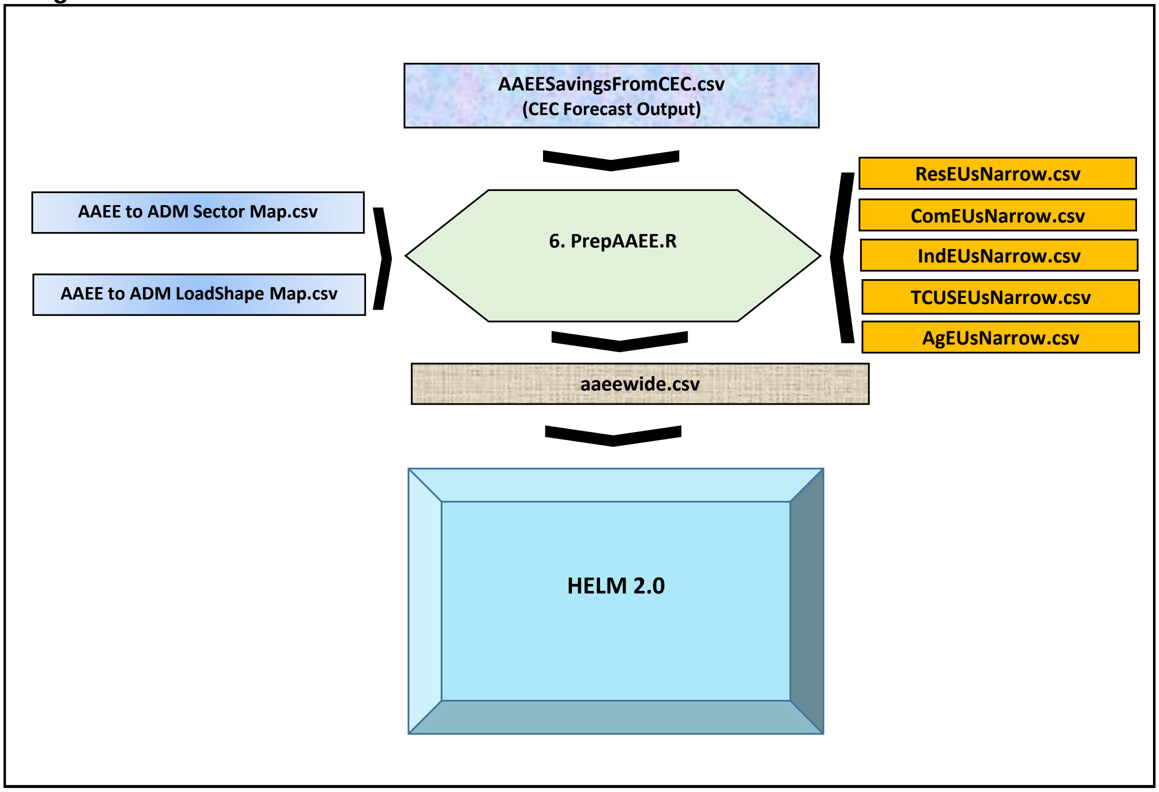
Source: ADM Associates, Inc.

The weights in the above table were developed based on expert judgment of ADM staff with extensive experience in commercial lighting projects, particularly in new construction applications. It is important to note, however, that the weights shown herein are fed into simple load-shape assignment tables and can be readily updated by Commission Staff if needed. The tables for AAEE and committed savings are provided in Appendix B.

Distribution of Impacts by Building and Zone

Note that the energy savings from AAEE and committed savings are provided at the utility service area rather than at the forecast zone level. Additionally, the energy savings are not broken out by building type within a sector. ADM has developed scripts to distribute the energy savings into forecast zones and building types. This process is depicted in Figure 216. In this process, the AAEE savings data are provided in the file *AAEESavingsFromCEC.csv*, and are in the format shown in Table 13. The two files on the left are used to enforce naming conventions and to disaggregate end-use level savings into specific energy efficiency load impact profiles as described in the previous section. The five files on the right side of the figure are energy usages by building, forecast zone, end-use, and year from the main CED Model. These files have been reformatted to facilitate the calculations within the *PrepAAEE.R* script. The resultant file is shown as *aaeewide.csv*, and is in the format required by HELM 2.0.

Figure 216: Schematic of the Process to Conform AAEE Data into the HELM 2.0 Format



A schematic of the process to conform AAEE forecast data into the HELM 2.0 format.

Source: ADM Associates, Inc

Apart from mapping end-uses to load impact profiles, the main operation in the *PrepAAEE.R* script is to disaggregate the AAEE impacts into the year/forecast zone/sector/building/end-use/load shape format. This is accomplished by using the base forecast elements at the zone/sector/building/end-use level.

For a given sector and end-use, the weights at the building and forecast zone level are calculated as follows:

$$Weight_{BZ} = \frac{\sum_{U,S,Y,B,Z} GWh}{\sum_{U,S,Y} GWh}$$

Where:

- **U** denotes utility service territory
- **S** denotes sector
- **Y** denotes year
- **B** denotes building type
- **Z** denotes forecast zone.

For example, if large offices in forecast zone 1 are expected to account for 3% of the energy use for the PG&E service territory in 2020, the team expects 3% of the energy savings to also accrue to large offices.

ADM has developed a similar process for committed energy savings. As of this writing, the Energy Commission is updating the CED Model, and it is possible that the updated model may provide AAEE and committed savings data at the same resolution as the load forecast. The scripts and map files are provided to Energy Commission staff in case the AAEE and committed savings will continue to be developed as they have been for the 2017 forecast.

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ACRONYMS AND ABBREVIATIONS

Acronym	Definition
AAEE	Additional Achievable Energy Efficiency
ADM	ADM Associates, Inc.
AG & PUMP	Agriculture and pumping
AMI	Advanced metering infrastructure
AWS	Airport weather station
CDD	Cooling degree day
CDH	Cooling degree hour
CED Model	California Energy Demand Forecast Model
CEUS	California Commercial End-use Survey
COP	Coefficient of performance
CPUC	California Public Utilities Commission
CSI	California Solar Initiative
DEER	Database of Energy Efficiency Resources
DOE	Department of Energy
E3	Energy and Environmental Economics, Inc.
EER	Energy efficiency ratio
Energy Commission	California Energy Commission
EPRI	Electric Power Research Institute
EV	Electric vehicles
EVIL Model	EV Infrastructure Load Model
GB	Gigabyte
GWh	Gigawatt hours
HDD	Heating degree day
HDH	Heating degree hour
HELM	Hourly Electric Load Model
HELM 2.0	Revised Hourly Electric Load Model
HVAC	Heating, ventilation, air conditioning
HVIP	California Hybrid and Zero Emission Truck and Bus Voucher Incentive Project
IEEE	Institute of Electrical and Electronics Engineers
IEPR	Integrated Energy Policy Report
IOU	Investor-owned utilities
kWh	Kilowatt hour
NAICS	North American Industry Classification System
NERC	North American Electric Reliability Corporation
NREL	National Renewable Energy Laboratory
NRMSE	Normalized root mean squared error
PC	Personal computer
PDT	Pacific Daylight Time
PG&E	Pacific Gas & Electric

POU	Privately-owned utilities
PST	Pacific Standard Time
PV	Photovoltaic
SAM	System Advisor Model
SCE	Southern California Edison
SDG&E	San Diego Gas & Electric
SEER	Seasonal energy efficiency ratio
TCU	Transportation, communications, and utilities
TMY	Typical meteorological year
TOU	Time of use
TV	Television
VSD	Variable speed drive

APPENDIX A: HELM 2.0 Manual

The HELM software is used to distribute forecasted energy use intensities (EUIs) throughout a given time frame on an hourly basis. The tool is equipped to provide various summaries of the hourly distribution, aggregated by sector and simulation year using dynamic loadshapes which are responsive to input weather data, economic predictors, and other exogenous data.

The transition from static to dynamic loadshapes necessitated significant revisions to the existing Hourly Electric Load Model (HELM). The revision process also represented an opportunity to 'modernize' other aspects of the existing software while streamlining the overall process. The existing HELM software (henceforth referred to as HELM 1.0) was built in FORTRAN and designed to run within an MS DOS instance under the windows operating system. HELM 1.0 consisted of several separate command line applications which took, as inputs, a myriad text base input files which defined the scenario(s) and their corresponding EUIs.

For HELM 2.0 ADM elected to base the code in the R statistical computing language and environment (More info can be found at https://www.r-project.org/about.html). This was done for several reasons, but the primary motivation was to employ an OS neutral environment with a robust community (and history) of support. This ensures that the basic software platform can receive maintenance and updates regardless of ADM's potential future involvement with the software – enabling independent support and maintenance by the Energy Commission. HELM 2.0 is coded in a modern/accessible scripting language which does not require separate compilers or access to low level components of the OS to update. Rather, any user can update the source code and distribute the updates in a relatively straightforward fashion.

The second objective in using the R environment was to simplify the overall process and automate many of currently manual steps required by HELM 1.0. Specifically, HELM 2.0 is developed as an R 'package' which makes all its components (including datasets) self-contained, easy to distribute, and simple to use. For example, functions are now built into the software which allow it to take, as inputs, the summary model outputs directly. Intermediate results are now stored in memory and reporting functions can be individually called to review the intermediate results, eliminating the need to wade through a myriad of text-based files on the hard drive to inspect the simulation results.

This chapter is written to provide readers with an overview of the HELM 2.0 model and its usage. Detailed descriptions of the functions and data sets within HELM 2.0 can be found in the manual pages (help files) included within its R package.

Installing the HELM

HELM 2.0 is distributed as a "source" package for the California Energy Commission. As such, it is not distributed by CRAN or any publicly available R repository. Instead, it is provided directly to the Energy Commission as a ".tar.gz" file and must be manually installed to the user's package library using the following code:

```
pathto <- "file path/to package file/helm_2.0.5.tar.gz"
install.packages(pathto,repos=NULL, type="source")
```

Note that the first line of code is used to store the full file path, locating the HELM package file on the hard-drive, into a variable called *pathto* which is then called in the function *install.packages()*. While this step is not technically necessary, it does clean up the code considerably, making it easier to read. Finally, note that the separator used to denote folders and subfolders within the file path are forward slash characters ("/") and not the standard backslash ("\") characters used in Windows file paths.

Running the HELM: Input Data and Formats

Input Files

It was noted in the introduction to this chapter that HELM 2.0 was written with the assumption that its input files would be in the same format as found in the Summary Model outputs. This is not strictly true however as HELM2.0 actually 'translates' the Summary Model outputs into separate *.csv* formatted files more conducive to the hourly endues peak reporting process. Thus the input process can be separated into two steps:

1) Convert Summary Model output into a HELM model input using the `processSummaryInputs()` function.
2) Run HELM on the desired scenario using the `readScenario()` function.

It is intended that the Summary Model file processed in step one specifies the entire scenario that the user intends to run in step two (e.g. Planning Areas, Forecast Zones, Sectors, etc.). While the final HELM input file can be manually modified to adjust the scenario to be modeled, it is not recommended due to the possibility of introducing user error within an otherwise systematic process.

The Summary Model outputs are .csv formatted data files with the following structure:

Field Name	Description
Sector	A string representing the name of the sector to which the listed EUIs apply
PA	A numeric code representing the planning area to which the listed EUIs apply
Zone	A numeric code representing the Forecast Zone to which the listed EUIs apply *(only defined for non-commercial or residential sectors)*
FZ	A numeric code representing the Forecast Zone to which the listed EUIs apply *(Applicable to commercial and residential sectors only)*
Group Number	A numeric code representing the 'Building Type' to which the listed EUIs apply *(only defined for non-commercial or residential sectors)*

Field Name	Description
Building Type	A numeric code representing the 'Building Type' to which the listed EUIs apply *(Applicable to commercial and residential sectors only)*
Group NAICS	A numeric code representing the 'End Use' to which the listed EUIs apply. *(only defined for non-commercial or residential sectors)*
End Use	A numeric code representing the 'End Use' to which the listed EUIs apply. *(Applicable to commercial and residential sectors only)*
Year	The year for which the listed EUIs apply
GWh High	The forecasted EUI assuming a 'high usage' scenario for the Sector, Planning Area, Forecast Zone, Building Type, End Use, and year defined in neighboring fields.
GWh Mid	The forecasted EUI assuming a 'mid usage' scenario for the Sector, Planning Area, Forecast Zone, Building Type, End Use, and year defined in neighboring fields.
GWh Low	The forecasted EUI assuming a 'low usage' scenario for the Sector, Planning Area, Forecast Zone, Building Type, End Use, and year defined in neighboring fields.

Example code to execute a HELM 2.0 model run is provided below:

```
################################################
#  1) Translate Summary Model Input File      #
################################################
setwd("File Path/To HELM Simulation/Working Directory")
SummaryInputDirectory <- "File Path/To Summary Model/Output File Directory"
SummaryInputFilename <- "NameOfSummaryModelFile.csv"
SaveDirectory <- "DirectoryToStoringHELMInput"

processSummaryInputs(SummaryInputDirectory, SummaryInputFilename,
SaveDirectory)

###########################################################
#  2) Read In Inputs and Generate Loadshapes for Scenario #
###########################################################
setwd("File Path/To HELM Simulation/Working Directory")
InputFilename <- "DirectoryToStoringHELMInput/InputFile.csv"

MyScenario <- readScenario(InputFilename)
```

It should be noted that the user must take special care regarding file-paths within the HELM model. All file paths defined by the user are considered to be relative to the working directory (defined by the `setwd()` function) unless the complete file path, including the drive designation, is provided.

Weather Data

Weather data for this tool was gathered from several resources. The primary data source is the NOAA (https://www.noaa.gov/). NOAA data was processed using some scripts of the own for downloading and cleaning, and the Energy Commission provided some processed weather data from their own weather processing resource. The System Advisor Model (https://sam.nrel.gov/) was used to obtain some specific fields like solar insolation and humidity. Typical weather from resources like the National Solar Radiation Database (https://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/tmy3/) provided files used when typical hourly weather was used for developing HELM 2.

Weather Data for Forecasting

For forecasting, a base year of weather is modified to represent weather for future years. Specifically, the holiday dates are updated, adjustments for leap years are made, day of the week is shifted, and daylight savings dates are accounted for.

Weather Data for Benchmarking

Weather data for the years 2014-2016 were obtained for various weather stations from NOAA resources and-used for benchmarking. Representative weather stations within each zone were download and weighted to model the climate zone. The weights are listed in the Table A-1.

Table A-1: Modeled Climate Zone

Zone No.	Climate Zones	Weather Stations	Summer Intrazonal Weight	Winter Intrazonal Weight	Spring/Fall Weight
1	Greater Bay Area	OAKLAND METRO INTL AP	26.73%	57.44%	42.73%
1	Greater Bay Area	SAN JOSE AP	73.27%	42.56%	57.27%
2	North Coast	UKIAH MUNI AP	100.00%	100.00%	100.00%
3	North Valley	RED BLUFF MUNI AP	100.00%	100.00%	100.00%
4	Central valley	SACRAMENTO EXECUTIVE AP	100.00%	100.00%	100.00%
5	Southern Valley	FRESNO YOSEMITE INTL AP	100.00%	100.00%	100.00%
6	Central Coast	SAN LUIS OBISPO AP	100.00%	100.00%	100.00%
7	LA Metro	BURBANK AP	47.43%	50.00%	49.22%
7	LA Metro	LONG BEACH DAUGHERTY FLD	52.57%	50.00%	50.78%
8	Big Creek West	SANTA BARBARA MUNI AP	100.00%	100.00%	100.00%
9	Big Creek Eest	BAKERSFIELD MEADOWS FIELD	100.00%	100.00%	100.00%
10	Northeast	RIVERSIDE MUNI AP	100.00%	100.00%	100.00%
11	Eastern	RIVERSIDE MUNI AP	100.00%	100.00%	100.00%
12	SDG&E	SAN DIEGO LINDBERGH FLD	33.33%	33.33%	33.33%
12	SDG&E	SAN DIEGO MIRAMAR WSCMO	33.33%	33.33%	33.33%
12	SDG&E	GILLESPIE FIELD	33.33%	33.33%	33.33%

During the benchmarking process usually models were developed with part of the benchmarking data and performance was tested using a subset of weather data set aside for verification.

Economic Descriptors

The economic inputs for Industrial and Mining and Extraction were GSP and EMP values at a quarterly resolution, while TCU used annual economic inputs. The economic data used for all Industrial facilities are gross state product (GSP) values in units of current-day millions of dollars. The economic data used for Mining and Oil and Gas Extraction were employment values in units of thousands of employees while GSP was provided for Petroleum. The economic data used for Air Transportation, Broadcasting, National

Security, Pipelines, and Utilities were employment values in units of thousands of employees, while total population in units of thousands were used for all other TCU facilities.

Supporting Data

In addition to the weather data and economic data, the dynamic loadshapes rely on several data sets for their reconstitution:

1) basetemps_commercial - CDD and HDD bases for commercial buildings
2) basetemps_residential - CDD and HDD bases for residential buildings
3) aggCoef - Loadshape Generator Coefficients for agricultural buildings/enduses
4) IND_MIN_TCU_coef - Loadshape Generator Coefficients for Industrial, Mining, and TCU buildings/enduses
5) commCoef - Loadshape Generator Coefficients for commercial buildings/enduses
6) ResCoef - Loadshape Generator Coefficients for residential buildings/enduses
7) ResScalar - Loadshape Generator Scalar Coefficients for residential buildings/enduses
8) StaticCoef – Loadshape Generator 8760 profiles for static loadshapes
9) PeakFactors.df - Table of annual peak calibration targets (historical observations)

Aside from the `PeakFactors.df` data source, all other data was developed based on the simulation and calibrations processes described elsewhere in this report. As such, it is advised that any updates/revisions to those data sources be treated comprehensively and no data source be manually edited in isolation from the others.

`PeakFactors.df` is intended to be annually updated to include historically observed system peak data, at the sector, forecast zone, and planning area, level for calibration purposes. As such, user update functions are included to maintain this data set.

Output Formats

The HELM model is designed to save all scenario data into a `helm_scenario` object. This is a reference class representing the entire scenario loaded into HELM for analysis. Each field of this class represents the attributes expected of any given HELM analysis. This conveniently stores all of the data generated from a particular input file into a single object within the R environment. The user can elect to save this to the hard drive for use later using the base package `save()` and `load()` functions. This is convenient as the overall scenario is written an external representation of the R object(s) to the specified file which can be quickly re-loaded at a later date – eliminating the need to re-run the entire scenario. While the updated HELM code is much faster than the previous software, it can still take several tens of minutes to execute a large scenario. Example code for this is provided below:

```
MyScenario <- readScenario(InputFilename)
```

```
save(MyScenario, file="Path To/User Save Location/Filename.rda")
load(file="Path To/User Save Location/Filename.rda")
```

Specific reporting functions are now included in HELM which generate target analytics and reporting outputs for the Energy Commission forecasting process. The report_annual() function generates annual peak forecast estimates for each year within the current scenario, reported by sector for each planning area and forecast zone. Peak estimates are reported with the calibration constant determined by comparing the raw helm estimates to the historical observations found in the `PeakFactors.df` data source.

The annual report is generated as a dataframe object within R and saved to the user defined R name/placeholder. This can be further reviewed within R or saved directly to the hard drive as a .csv file. Example code provided below:

```
annual_report <- report_annual(MyScenario$Hourly)
```

```
OutputAnnualReport <- "Path To/Reporting Directory/MyScenario_peakReport.csv"
write.csv(annual_report, OutputAnnualReport)
```

The formatted annual report .csv file is organized into the following structure:

Troubleshooting and Support

ADM expects that the HELM 2.0 source code will continue to be honed through the next Energy Commission forecast as this will be its first application in the forecasting process. As such, troubleshooting and bug reports can be directed to Steven Keates (Steven@admenergy.com) or Daniel Chapman (daniel.chapman@admenergy.com) at ADM Associates throughout the summary of 2019.

APPENDIX B:
End-Use to Load Shapes Maps

AAEE Map from Potential and Goals Study

Codes and standards are mapped from end-uses to efficient load shapes through review of the Potential and Goals Study (Wikler et al. 2017) measure level results viewer file. To determine the weights and shapes in this file, analysts first reviewed cumulative energy savings through 2030 by end-use, and assigned load shapes to all measures (Table B-1). Not all measures have specific load shapes available, so ADM must select the most appropriate load shape from the available arsenal. For example, the television load shape is used to describe set top boxes, video game consoles, and DVD players as well as televisions. Weights are determined as the total energy savings through 2030 attributable to a given load shape, within a given end-use.

Table B-1: Map of AAEE Measures from the Potential and Goals Study

Sector	Savings Type	End-use	Efficiency Load Shape	Weight
Commercial	Utility Programs	Lighting	Indoor.Lighting.Eff	92.5%
Commercial	Utility Programs	Lighting	Outdoor.Lighting	6.4%
Commercial	Utility Programs	Lighting	Occsensor.Eff	1.0%
Commercial	Utility Programs	Lighting	Daylighting.Eff	0.2%
Commercial	Utility Programs	HVAC	Cooling	75.0%
Commercial	Utility Programs	HVAC	Economizer.Eff	9.9%
Commercial	Utility Programs	HVAC	HeatPump.Eff	12.6%
Commercial	Utility Programs	HVAC	Ventilation	2.5%
Commercial	Utility Programs	ComRefrig	Refrigeration	85.3%
Commercial	Utility Programs	ComRefrig	Flat	14.7%
Commercial	Utility Programs	WholeBlg	WholeBuilding	100.0%
Commercial	Utility Programs	WholeBlgB	WholeBuilding	100.0%
Commercial	Utility Programs	AppPlug	Miscellaneous	100.0%
Commercial	Utility Programs	FoodServ	Cooking	100.0%
Commercial	Utility Programs	Data Center	Flat	100.0%
Commercial	Utility Programs	WaterHeat	Water.Heating	100.0%
Commercial	Utility Programs	MachDr	Miscellaneous	100.0%
Commercial	Utility Programs	BldgEnv	Cooling	100.0%
Commercial	Codes Standards and Other	Lighting	Indoor.Lighting.Eff	56.9%
Commercial	Codes Standards and Other	Lighting	Outdoor.Lighting	7.4%
Commercial	Codes Standards and Other	Lighting	Occsensor.Eff	28.0%
Commercial	Codes Standards and Other	Lighting	Daylighting.Eff	4.4%
Commercial	Codes Standards and Other	Lighting	Flat	3.3%
Commercial	Codes Standards and Other	HVAC	Cooling	64.3%
Commercial	Codes Standards and Other	HVAC	HeatPump.Eff	18.8%
Commercial	Codes Standards and Other	HVAC	Ventilation	10.3%

Sector	Savings Type	End-use	Efficiency Load Shape	Weight
Commercial	Codes Standards and Other	HVAC	Flat	6.6%
Commercial	Codes Standards and Other	ComRefrig	Refrigeration	100.0%
Commercial	Codes Standards and Other	WholeBlg	WholeBuilding	100.0%
Commercial	Codes Standards and Other	WholeBlgB	WholeBuilding	100.0%
Commercial	Codes Standards and Other	AppPlug	Miscellaneous	100.0%
Commercial	Codes Standards and Other	FoodServ	Cooking	100.0%
Commercial	Codes Standards and Other	Data Center	Flat	100.0%
Commercial	Codes Standards and Other	WaterHeat	Water.Heating	100.0%
Commercial	Codes Standards and Other	MachDr	Miscellaneous	100.0%
Commercial	Codes Standards and Other	BldgEnv	Cooling	100.0%
Commercial	Codes Standards and Other	ProcHeat	Miscellaneous	100.0%
Residential	Utility Programs	Lighting	ResLighting.Eff	91.6%
Residential	Utility Programs	Lighting	ResOccsensor.Eff	8.4%
Residential	Utility Programs	AppPlug	Dryer	54.7%
Residential	Utility Programs	AppPlug	Refrigerator	43.1%
Residential	Utility Programs	AppPlug	Washer	1.7%
Residential	Utility Programs	AppPlug	Miscellaneous	0.5%
Residential	Utility Programs	WholeBlg	WholeBuilding	100.0%
Residential	Utility Programs	WholeBlgB	WholeBuilding	100.0%
Residential	Utility Programs	HVAC	Cooling.Eff	67.9%
Residential	Utility Programs	HVAC	Heat.Pump.Eff	32.1%
Residential	Utility Programs	FoodServ	Cooking	100.0%
Residential	Utility Programs	WaterHeat	Water.Heating	100.0%
Residential	Utility Programs	BldgEnv	Windows.Eff	41.4%
Residential	Utility Programs	BldgEnv	Insulation.Eff	58.6%
Residential	Codes Standards and Other	Lighting	ResLighting.Eff	100.0%
Residential	Codes Standards and Other	AppPlug	Pool.Pump	49.7%
Residential	Codes Standards and Other	AppPlug	Television	32.5%
Residential	Codes Standards and Other	AppPlug	Miscellaneous	8.9%
Residential	Codes Standards and Other	AppPlug	Refrigerator	7.0%
Residential	Codes Standards and Other	AppPlug	Washer	1.8%
Residential	Codes Standards and Other	WholeBlg	WholeBuilding	100.0%
Residential	Codes Standards and Other	WholeBlgB	WholeBuilding	100.0%
Residential	Codes Standards and Other	HVAC	Cooling.Eff	65.9%
Residential	Codes Standards and Other	HVAC	Heat.Pump.Eff	34.1%
Residential	Codes Standards and Other	WaterHeat	Water.Heating	100.0%
Residential	Codes Standards and Other	BldgEnv	Windows.Eff	100.0%
Residential	Codes Standards and Other	FoodServ	Cooking	100.0%

Map and relative weight of AAEE measures from the Potential and Goals Study.

Source: ADM Associates, Inc.

Committed Savings

Energy savings from end-uses listed in Committed EE are provided at the utility, sector, and end-use level. The table below is used to assign load impact profiles to end-uses. The weights derived specifically for utility sponsored programs from the Potential and Goals study are applied to committed savings (Table b-2).

Table 15: Map of Committed Savings Measures from the Potential and Goals Study

Sector	Committed EE End-use	End-use	Weight
Agriculture and Water	Agricultural	WholeBuilding	100.0%
Commercial	Building Shell	WholeBuilding	100.0%
Commercial	CFL	Indoor.Lighting.Eff	100.0%
Commercial	HVAC (Non-Shell)	Cooling	75.0%
Commercial	HVAC (Non-Shell)	Economizer.Eff	9.9%
Commercial	HVAC (Non-Shell)	HeatPump.Eff	12.6%
Commercial	HVAC (Non-Shell)	Ventilation	2.5%
Commercial	Lighting (Non-CFL)	Indoor.Lighting.Eff	92.5%
Commercial	Lighting (Non-CFL)	Outdoor.Lighting	6.4%
Commercial	Lighting (Non-CFL)	Occsensor.Eff	1.0%
Commercial	Lighting (Non-CFL)	Daylighting.Eff	0.2%
Commercial	New Construction	WholeBuilding	100.0%
Commercial	Other	Miscellaneous	100.0%
Commercial	Pre-1998	WholeBuilding	100.0%
Commercial	Refrigeration	Refrigeration	100.0%
Commercial	Unspecified	Miscellaneous	100.0%
Commercial	Water Heating	Water.Heating	100.0%
Industrial	Industrial	WholeBuilding	100.0%
Residential	Building Shell	WholeBuilding	100.0%
Residential	CFL	ResLighting.Eff	100.0%
Residential	HVAC (Non-Shell)	Cooling.Eff	100.0%
Residential	Lighting (Non-CFL)	ResLighting.Eff	100.0%
Residential	New Construction	WholeBuilding	100.0%
Residential	Other	WholeBuilding	100.0%
Residential	Pool Pump	Pool.Pump	100.0%
Residential	Pre-1998	WholeBuilding	100.0%
Residential	Refrigeration (Non-Recycling)	Refrigerator	100.0%
Residential	Refrigerator Recycling	Refrigerator	100.0%
Residential	Unspecified	Miscellaneous	100.0%
Residential	Water Heating	Water.Heater	100.0%

Map and relative weight of committed savings measures from the Potential and Goals Study.

Source: ADM Associates, Inc.